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Resource Allocation for UAV-Aided Disaster Emergency Communication

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Abstract

This dissertation explores the utilization of Unmanned Aerial Vehicles (UAVs) for expanding wireless coverage in civilian applications, particularly real-time moni-toring, search and rescue, and disaster response. UAVs can function as aerial base stations, restoring connectivity during emergency cellular network outages. They can also augment existing ground infrastructure to enhance coverage and data rates for users. However, limited battery capacity necessitates periodic re-charging of UAVs. This dissertation addresses the challenge of minimizing the number of UAVs required for continuous coverage of a designated area, consider-ing the con-straints of recharging time, travel time, and the number of subareas encompassed by a single patrol cycle. Due to the inherent complexity of the prob-lem, a graph-partitioning approach is proposed. The coverage graph is divided into cy-cles originating from the charging station, and the minimum number of UAVs needed to traverse such a cycle is determined based on the parameters above. An efficient algorithm is then developed to solve this optimization prob-lem.

The dissertation subsequently investigates the optimal placement of a single UAV for minimizing the total transmission power required to ensure wireless cov-erage for indoor disaster victims. Two practical scenarios are analyzed, and effi-cient solutions are presented for each. Recognizing the limitations of a single UAV's transmit power, the dissertation further explores minimizing the number of UAVs needed for comprehensive indoor coverage. An efficient algorithm is pro-posed to address this challenge.

Finally, the dissertation examines the maximization of indoor wireless cov-erage using UAVs equipped with directional antennas. To prevent signal interfer-ence while operating on a single channel, non-overlapping coverage areas are pri-oritized. Two deployment methods are presented for UAV placement, consid-ering coverage from one or both building sides. The results demonstrate that strategi-cally placing UAVs in an upside-down configuration can significantly im-prove total coverage compared to single-sided deployment.

Keywords

Unmanned Aerial Vehicle (UAV); Communication; Resource Allocation.

1. Introduction

1.1. Background and Significance

UAVs can be used in many civilian applications due to their ease of deployment, low maintenance cost, high mobility and ability to hover [2]. Such vehicles are being used for real-time monitoring of road traffic, remote sensing, search and rescue operations, delivery of goods, security and surveillance, precision agriculture, and civil infrastructure inspection. They can also be used as aerial wireless base stations to complement existing cellular network service by providing additional capacity to hotspot areas during special events [3] or to provide wireless coverage when cellular networks are not operational due to natural disasters [4]. Cell on wheels (COWs) are typically used to provide expanded wireless coverage for short-term demands when cellular coverage is either minimal, never present or compromised by disaster, as shown in Figure 1.1. Compared to the COWs, the advantage of using UAV-based aerial base stations is their ability to quickly and easily move during emergency cases [5]. They can move to 3D efficient placements that optimize several objective functions of interest and update their placements based on user distribution changes.The authors in [9] classify UAVs into four categories based on their altitudes and their wing types, each with its own strengths and weaknesses. The first category is the high-altitude platforms (HAPs). HAPs are designed for long-duration flights counted in months at altitudes above 17 km. They are typically utilized to provide wide wireless coverage for remote geographic areas. However, they are costly, and their deployment time is significantly longer. The second category is the low altitude platforms (LAPs). LAPs are flexible and can fly at altitudes of up to a few kilometres. They are typically utilized to provide wireless coverage during emergency cases or to collect data from ground sensors. On the other hand, they need to return periodically to a charging station for recharging, due to their limited battery capacity. The third category is the fixed-wing UAVs. Fixed-wing UAVs have high speed and more payload, but they need to maintain a continuous forward motion in order to remain aloft, they are not appropriate for stationary use cases. The fourth category is the rotary-wing UAVs. Rotary-wing UAVs can hover and stay stationary in the air [10], but they have limited payload. In Table 1.1, we present the types of UAVs and their capabilities.

1.2. UAV Classification

The authors in [9] classify the UAVs into four categories based on their altitudes and them. wing types, each with its own strengths and weaknesses. The first category is the high-altitude platforms (HAPs). HAPs are designed for long-duration flights counted in months at altitudes above 17 km. They are typically utilized to provide wide wireless coverage for remote geographic areas. However, they are costly, and their deployment time is significantly long. The second category is the low altitude platforms (LAPs). LAPs are flexible and can fly at altitudes of up to a few kilometers. They are typically utilized to provide wireless coverage during emergency cases or to collect data from ground sensors. On the other hand, they need to return periodically to a charging station for recharging, due to their limited battery capacity. The third category is fixed-wing UAVs. Fixed-wing UAVs have high speed and more payload, but they need to maintain a continuous forward motion to remain aloft, they are not appropriate for stationary use cases. The fourth category is rotary-wing UAVs. Rotary-wing UAVs can hover and stay stationary in the air [10], but they have limited payload. we present the types of UAVs and their capabilities.

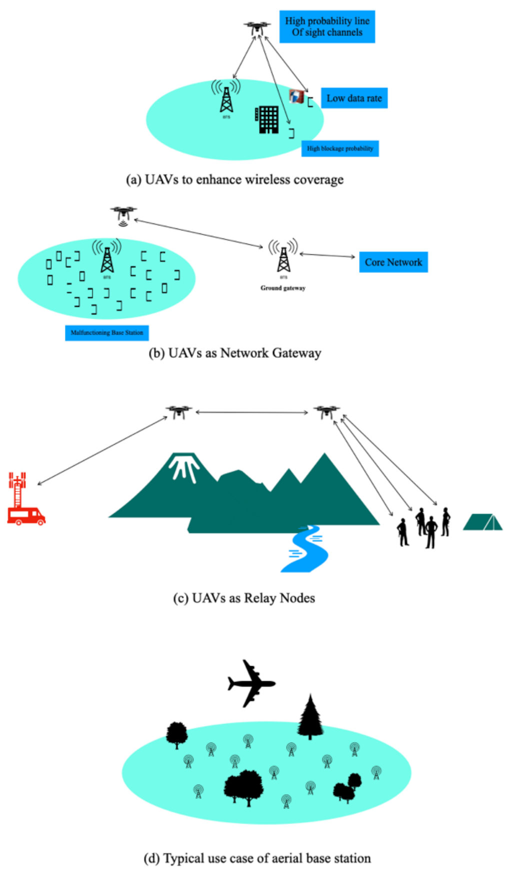

Figure 1.1 Typical use cases of aerial base stations.

1.3. UAV Use Cases

The authors in [10–12] present the typical use cases of aerial wireless base stations. Some of the UAV use cases are as follows:

• UAVs to enhance the wireless coverage: UAVs can be utilized to supplement the ground base station to provide high probability line of sight channels when the location of the user has a high blockage probability or low data rate due to the high path loss.

• UAVs as network gateways: In remote geographic areas or disaster-stricken areas, UAVs can be used as gateway nodes to provide connectivity to backbone networks, communication infrastructure, or the Internet.

• UAVs as relay nodes: UAVs can be utilized as relay nodes to provide wireless connectivity between two or more distant wireless devices without reliable direct communication links.

• UAVs for data collection: UAVs can be utilized to gather delay-tolerant information from many distributed wireless devices. An example is to collect data from wireless sensors in precision agriculture.

1.4. Dissertation Outline and Objective

We start by studying the continuous coverage problem in Chapter 3. In the continuous coverage problem, we aim to minimize the number of UAVs required for continuous coverage of a given area, given the recharging requirements. Due to the intractability of the problem, we study partitioning the coverage graph into cycles that start at the charging station. We first characterize the minimum number of UAVs to cover such a cycle based on the charging time, the travelling time, and the number of subareas to be covered by the cycle. Based on this analysis, we then develop an efficient algorithm, the cycles with limited energy algorithm. The straightforward method to continuously cover a given area is to split it into N subareas and cover it by N cycles using N additional UAVs. We demonstrate that the cycles with limited energy algorithm require 69%-94% fewer additional UAVs relative to the straightforward method, as the energy capacity of the UAVs is increased, and 67%-71% fewer additional UAVs, as the number of subareas is increased.

In Chapter 4, we study the problem of efficient placement of a single UAV, where the objective is to minimize the total transmit power required to cover indoor disaster users. The formulated problem is generally difficult to solve. To that end, we consider three cases of practical interest and provide efficient solutions to the formulated problem under these cases. Then, we study the problem of minimizing the number of UAVs required to provide wireless coverage to indoor users in disasters and prove that this problem is NP-complete. Due to the intractability of the problem, we use clustering to minimize the number of UAVs required to cover indoor users. In our proposed algorithm, we check if the maximum transmit power of a UAV is sufficient to cover each cluster. If not, the number of clusters is incremented by one, and the problem is solved again. In the uniform split method, we split the building into k regular structures and utilize k UAVs to provide wireless coverage for indoor users regardless of user distribution. We demonstrate through simulations that the method that splits the building into regular structures requires 80% more UAVs relative to our proposed algorithm. The dissertation is finally concluded in Chapter 5.

1.5. Significance and Issues of Resource Allocation for UAV-Aided

UAVs (Unmanned Aerial Vehicles) are transforming various applications due to their flexibility and mobility. However, efficiently utilizing their capabilities hinges on effective resource allocation. Here's a breakdown of the significance and issues surrounding resource allocation in UAV-aided systems:

Significance:

Enhanced Network Performance: Resource allocation algorithms can optimize factors like power, bandwidth, and flight paths of UAVs. This leads to improved network coverage, increased data transmission rates, and better signal quality for users on the ground.

Extended UAV Range and Endurance: By optimizing resource allocation, UAVs can minimize energy consumption during flight and communication. This translates to longer flight times and a wider operational range for UAVs before needing to recharge.

Improved System Efficiency: Resource allocation algorithms can take into account factors like user demand, real-time network conditions, and UAV capabilities. This ensures resources are directed towards areas with the highest need, leading to a more efficient overall system.

Support for Diverse Applications: Different UAV applications have varying resource requirements. Resource allocation algorithms can be tailored to specific needs, enabling UAVs to effectively support tasks like search and rescue, disaster response, environmental monitoring, and precision agriculture.

Issues:

Dynamic Environment: Both the user demands, and environmental conditions can change rapidly. Resource allocation algorithms need to be adaptable to handle these dynamic changes efficiently.

Limited Battery Capacity: UAVs are typically battery-powered, and their flight time is limited. Resource allocation algorithms must prioritize tasks while minimizing energy consumption.

Security and Privacy Concerns: UAVs can collect sensitive data. Resource allocation strategies need to consider security measures to protect data transmission and user privacy.

Complexity of Multi-UAV Systems: Coordinating resource allocation across multiple UAVs operating in the same airspace introduces additional complexity. Algorithms need to be designed to avoid interference and ensure efficient collaboration between UAVs.

1.6. Research Questions

Considering the major concerns in the first subsection, we aim to answer the following questions practically.

- How can resource allocation algorithms be designed to maximize network coverage and data transmission rates in disaster zones with damaged infrastructure?
- How can resource allocation strategies adapt to dynamic changes in user demand and network conditions during a disaster event?
- What are the trade-offs between maximizing network capacity and minimizing energy consumption for UAVs deployed in disaster response?
- How can resource allocation strategies be optimized to extend the operational range and flight time of UAVs in disaster zones with limited infrastructure for recharging?
- Can machine learning techniques be used to develop real-time resource allocation algorithms that adapt to the evolving needs of a disaster situation?
- How can resource allocation algorithms be designed to coordinate the deployment and communication of multiple UAVs in a disaster zone to avoid interference and optimize airspace utilization?
- How can resource allocation algorithms be designed to seamlessly integrate UAV communication with existing, potentially damaged, disaster response infrastructure?

2. Continuous Wireless Coverage Using UAV

In 20051, Hurricane Katrina in the United States caused over 1,900 deaths, 3 million landline phone interruptions, and more than 2,000 base stations going out of service [4,30,31]. Another example of a large-scale interruption of telecommunications service is the World Trade Center attack in 2001 when it took just minutes for the nearby base stations to be overloaded. The attacks caused the disturbance of a phone switch with over 200,000 lines, 20 cell sites, and 9 TV broadcast stations [4, 32]. These incidents demonstrate the need for quick/efficient deployment networks for emergency cases.

The authors in [33] propose a UAV-based replacement network during disasters, where the UAVs serve as aerial wireless base stations. However, this study does not consider how the UAVs will guarantee continuous coverage when they need to return to the charging station for recharging. Though a UAV has limited energy capacity and needs to recharge its battery before running out of energy during the coverage process, only a few studies have considered this constraint in the UAV coverage problem. Concretely, the author in [34] determines the minimum number of UAVs that can provide continuous coverage for a single area using identical and non-identical UAVs. However, no consideration has been made for the case when there are multiple subareas that need to be covered, which is the typical scenario during disasters. The author in [35] formulates the mobile charging problem, in which multiple mobile chargers collaborate to charge static sensors with a minimum number of mobile chargers subject to the speed and energy limits of the mobile chargers. In this problem, the chargers will not cover the sensors continuously. The mobile charger will visit the sensor and stay for a specific time to charge the sensor. After finishing the charging process, it will visit the other sensors. In [36], the authors study the continuous coverage problem for mobile targets. During the coverage process, a UAV that runs out of energy is replaced by a new one.

Many studies [13,14,37,38] focus on minimizing the total transmission power of the UAVs during the coverage of a geographical area, however, no limits on the UAV energy capacity and the need for recharging have been considered. The work in [39] reports that the energy consumption during data transmission and reception is much smaller than the energy consumption during the UAV hovering, i.e., it only constitutes 10%-20% of the UAV energy capacity. Thus, it is important to conduct studies that consider the energy consumption during the UAV hovering rather than focusing on minimizing the energy consumption during data transmission and reception.

Contrary to the related work above, we integrate the recharging requirements into the coverage problem and examine the minimum number of required UAVs for enabling continuous coverage under that setting.

2.1. System model of Continuous Wireless Coverage Using UAV

Consider a geographical area G={g1,...,gN}, where gi represents a subarea i, the subarea g1∈G includes the charging station and all subareas except subarea g1 need to be covered G0=G \ g1. We aim to find the minimum number of UAVs that can provide continuous coverage over G0 by placing the UAVs at locations where each UAV will provide full coverage for one subarea.

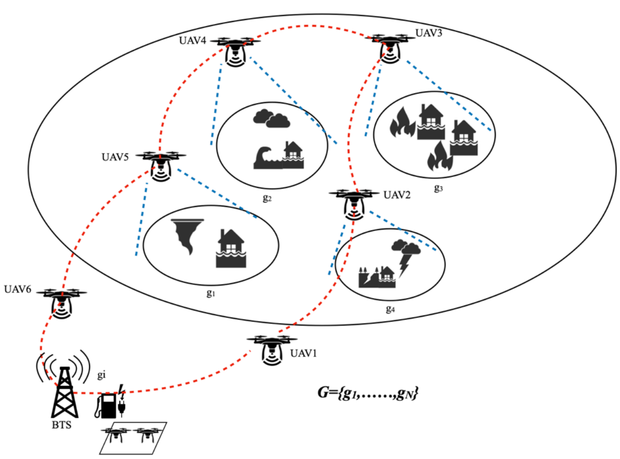

Figure 2.1 Providing continuous wireless coverage.

In the continuous coverage problem, we assume (1) Time slotted system in which the slot duration is 1-time unit and the total coverage duration is T. (2) All UAVs start the coverage process from the charging station and they need to return to the charging station after they complete the coverage process. (3) Each UAV has limited energy capacity E and it needs to return to the charging station to recharge the battery before running out of energy during the coverage process. (4) Each UAV can move (from the charging station to location i), (from location i to location j) or (from location j to the charging station) and this process will take a one-time slot. (5) Each UAV covers a given subarea for one or multiple time slots. (6) At each time slot, each subarea will be covered by only one UAV. (7) The UAV cannot travel to the charging station or to any other location until the handoff process is completed in which another UAV arrives to cover the subarea such that the continuous coverage is guaranteed. (8) The recharging process takes Tcharge at the charging station.

2.2. Problem Formulation of Continuous Coverage

In order to present the problem formulation, we introduce the binary variable xm that takes the value of 1 if the UAV m visits any subarea from charging station during the coverage duration T and equals 0 otherwise; the binary variable yitj,m that takes the value of 1 if the UAV m moves through edge ij during the time slot t and equals 0 otherwise; the binary variable zjt,m that takes the value of 1 if the UAV m covers the subarea j at time slot t and equals 0 otherwise

$$\min \sum_{m \in M} x_m$$

subject to

$$y^t_{ij,m} \leq x_m \qquad \forall i,j \in G, \forall t \in [0,T], \forall m \in M \tag{3.1}$$

$$z^t_{j,m} \leq x_m \qquad \forall j \in G_0, \forall t \in (0,T), \forall m \in M \tag{3.2}$$

$$\sum_{m \in M} y^0_{1j,m} = 1 \qquad \forall j \in G_0 \tag{3.3}$$

$$\sum_{m \in M} z^t_{j,m} = 1 \qquad \forall j \in G_0, \forall t \in (0,T) \tag{3.4}$$

$$\sum_{i \in G, i \neq j} \sum_{m \in M} y^t_{ij,m} \leq 1 \qquad \forall j \in G_0, \forall t \in [0,T] \tag{3.5}$$

$$\sum_{i_1 \in G} y^t_{i_1 j,m_1} = \sum_{i_2 \in G} y^{t+1}_{ji_2,m_2} \qquad \forall j \in G_0, \forall t \in (0,T), m_1 \neq m_2 \tag{3.6}$$

$$\sum_{m \in M} \sum_{t \in [0,T)} \sum_{i \in G} y^t_{ij,m} \leq \sum_{m \in M} \sum_{t \in (0,T)} z^t_{j,m} \qquad \forall j \in G_0 \tag{3.7}$$

$$\sum_{j \in G_0} \sum_{\tau \in T_{charge}} [y^t_{j1,m} + y^{t+\tau}_{1j,m}] \leq 1 \qquad \forall m \in M, \forall t \in (0,T) \tag{3.8}$$

$$\sum_{m \in M} \sum_{t \in [0,T]} \sum_{j \in G_0} y^t_{1j,m} = \sum_{m \in M} \sum_{t \in [0,T]} \sum_{i \in G_0} y^t_{i1,m} \tag{3.9}$$

$$\begin{aligned} &\sum_{t \in [t_1,t_2]} \sum_{i,j \in G} E^{Travel}_{ij} y^t_{ij,m} + \sum_{t \in [t_1,t_2]} \sum_{j \in G} E^{Cover}_j z^t_{j,m} \leq E \qquad \forall m \in M, \\ &\forall [t_1,t_2] \in [0,T], t_1 = arg\, y^t_{1j,m}, t_2 = arg\, y^t_{i1,m}, t_2 > t_1. \end{aligned} \tag{3.10}$$

The objective is to minimize the number of UAVs that are needed to provide a continuous coverage during the coverage duration T. Constraint sets (3.1) and (3.2) ensure that a UAV can travel and cover the subareas only if we select it to participate in the coverage process. Constraint set (3.3) ensures that all subareas will be covered at the first time slot. Constraint set (3.4) guarantees the continuous coverage for each subarea. Constraint set (3.5) allows the UAV to visit a new subarea (when yitj,m =1) or to continue covering the current subarea (when yitj,m=0). Constraint set (3.6) characterizes the handoff process between the UAVs, when the UAV m1 wants to visit the subarea j from subarea i1 at time t (yi1tj,m1 =1), the UAV m2 that covers the subarea j will travel to subarea i2 at time t + 1 (yi1t+1j,m1 =1). Constraint set (3.7) describes the relation between the traveling process and the covering process, where the number of times that the subarea j is covered will be greater than or equal to the number of times that it is visited. Constraint set (3.8) shows that the recharging process will take Tcharge at the charging station. Constraint (3.9) ensures that the number of UAVs outgoing from the charging station and the number of UAVs incoming to the charging station are the same after we complete the coverage process. Constraint set (3.10) shows that the energy capacity of a UAV can cover the wasted energy during the traveling and the covering processes in each cycle where t1 represents the time that a UAV travels from the charging station with full energy capacity and t2 represents the time that a UAV arrives to the charging station to charge the battery. Next, we prove that the continuous coverage problem is an NP-complete.

2.3 Heuristic Algorithm

Due to the intractability of the problem, we study partitioning the coverage graph into cycles that start at the charging station. We first characterize the minimum number of UAVs required to cover each cycle based on the charging time, the travelling time, and the number of subareas to be covered by the cycle. Our analysis is based on the uniform coverage in which a UAV covers each subarea in each cycle for a constant time. Based on this analysis, we then develop an efficient algorithm, the cycles with limited energy algorithm, that minimizes the required number of UAVs that guarantees continuous coverage.

2.4 Analysis

It is obvious that we need N UAVs to cover N subareas at any given time, but the question here is how many additional UAVs are needed to guarantee continuous coverage. In this subsection, we assume that a UAV visits the subareas based on a cycle that starts from the charging station and ends at the charging station for the charging process. We also assume that a given UAV covers the subareas in the cycle uniformly, in which a UAV covers each subarea in each cycle for a constant time. In Theorem 2, we find the minimum number of additional UAVs that are needed to guarantee continuous coverage for a cycle, which will help us while developing Algorithm 1.

Theorem 2. The minimum number of additional UAVs k that are required to provide continuous and uniform coverage for a cycle that contains n subareas must satisfy this inequality.

$$k\frac{T_{Coverage}}{n} \geq (n+1)T + T_{Charge},$$

Where TCoverage is the time that a UAV allocates to cover all subareas in the cycle, T is the time that a UAV needs to travel from subarea i to subarea j and Tcharge is the time that a UAV needs to recharge the battery at charging station.
Proof. Consider that all n subareas in the cycle are covered by n UAVs and the UAV that covers the last subarea wants to return to the charging station to recharge its battery. The handoff process needs to begin between one of the additional UAVs from the charging station and the UAV that covers the first subarea in the cycle.
The UAV that covers the last subarea needs to wait (n − 1) T to do the handoff process, during this time the additional UAVs are covering the first subarea. After the handoff process is completed, the UAV needs T time units to return to the charging station, Tcharge to recharge the battery and T to visit the first subarea in the cycle again. Then, we have:

$$k\frac{T_{Coverage}}{n} \geq (n-1)T + T + T_{Charge} + T$$

2.5 Performance Evaluation

We quantify the power consumption by UAV when it is hovering, travelling and transmitting data. The power consumption in watt by a UAV during hovering can be given by [42]:

$$P = 4\frac{T_h^{3/2}}{\sqrt{2QS}} + p,$$

where Th is the fourth of the quadcopter total weight in newton, Q is the density of the air in kg/m3, S is the rotor swept area in m2 and p is the power consumption of electronics in watt.

$$P = \frac{(m_p + m_v)v}{370\eta r} + p,$$

The power consumption in kW by a UAV during travelling can be given by [43]:
where mp is the payload mass in kg, mv is the vehicle mass in kg, r is the lift-to-drag ratio (equals 3 for the vehicle that is capable of vertical takeoff and landing), η is the power transfer efficiency for motor and propeller, p is the power consumption of

electronics in kW and v is the velocity in km/h.
The power consumption in dB by a UAV during data transmission can be given by [14]:

$$P_t(dB) = P_r(dB) + \bar{L}(R, h) \quad (3.11)$$

$$\bar{L}(R, h) = P(LOS) \times L_{LOS} + P(NLOS) \times L_{NLOS} \quad (3.12)$$

$$P(LOS) = \frac{1}{1 + \alpha.exp(-\beta[\frac{180}{\pi}\theta - \alpha])} \quad (3.13)$$

$$L_{LOS}(dB) = 20log(\frac{4\pi f_c d}{c}) + \xi_{LOS} \quad (3.14)$$

$$L_{NLOS}(dB) = 20log(\frac{4\pi f_c d}{c}) + \xi_{NLOS} \quad (3.15)$$

In equation (3.11), Pt is the transmit power, Pr is the required received power to achieve a SNR greater than threshold γth, $\bar{L}$(R, h) is the average path loss as a function of the altitude h and coverage radius R. In equation (3.12), P(LOS) is the probability of having line of sight (LOS) connection at an evaluation angle of θ, P(NLOS) is the probability of having non LOS connection and equals (1-P(LOS)), LLOS and LNLOS are the average path loss for LOS and NLOS paths. In equations (3.13-3.15), α and β are constant values which depend on the environment, fc is the carrier frequency, d is the distance between the UAV and user, c is the speed of the light , ξLOS and ξNLOS are the average additional losses which depend on the environment. In this chapter, we assume that the power wasted during data transmission is constant, where the power consumed by a UAV during data transmission and reception is much smaller than the power consumed during hovering or traveling [39].
Given a geographical area G , the number of the subareas that we need to cover and the density of the users, the question here is how to find the optimal boundaries of the subareas that will be covered by the UAVs. To answer this question, the authors of [13] utilize the transport theory to find the optimal boundaries of the subareas. Unfortunately, this approach needs to solve $\binom{N}{2}$ non-linear equations at each iteration, where N is the number of subareas. In this chapter, we divide the geographical area uniformly and apply the SM and CLE algorithms to find the minimum number of additional UAVs that provide continuous coverage. We study the effect of the UAV energy capacity, the grid size of the geographical area, the charging time and the travelling time on the number of additional UAVs. Table 3.7 lists the parameters used in the numerical analysis [44].

3. Wireless Coverage UAV

To use UAV as an aerial wireless base station1, the authors in [48] presented an Air-to-Ground path loss model that helped academic researchers formulate many important UAV-based coverage problems. The authors in [14] utilized this model to evaluate the impact of a UAV altitude on the downlink ground coverage and to determine the optimal values for altitude which lead to maximum coverage and minimum required transmit power. In [13], the authors used the path loss model to propose a power-efficient deployment for UAVs under the constraint of satisfying the rate requirement for all ground users. The authors in [18] utilized the path loss model to study the optimal deployment of multiple UAVs equipped with directional antennas, using circle packing theory. The 3D locations of the UAVs are determined in a way that the total coverage area is maximized. In [22], the authors used the path loss model to find the minimum number of UAVs and their 3D locations so that all outdoor ground users are served. However, it is assumed that all users are outdoors, and the location of each user can be represented by an outdoor 2D point. These assumptions limit the applicability of this model when one needs to consider indoor users.

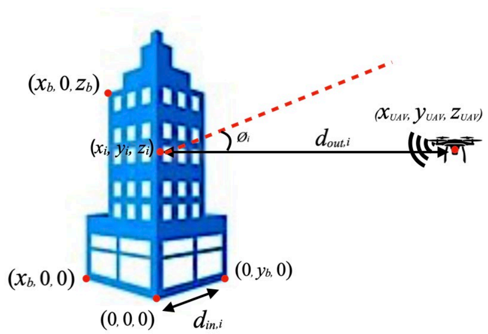

Figure 3.1 Parameters of the path loss model.

Providing good wireless coverage for indoor users is very important. According to Ericsson report [49], 90% of the time people are indoors and 80% of the mobile Internet access traffic also happens indoors [50, 51]. To guarantee wireless coverage, service providers are faced with several key challenges, including providing service to many indoor users and the ping-pong effect due to interference from nearby macro cells [52–54]. In this chapter, we propose using UAVs to provide wireless coverage for users inside a high-rise building after partial or complete infrastructure damage due to natural disasters or after base station offloading in extremely crowded events [10] (such as concerts, indoor sporting events, etc.), when the cellular network service is not available or unable to serve all indoor users.

3.1 System Model of Wireless Coverage UAV

Let (xUAV ,yUAV ,zUAV) denote the 3D location of the UAV. We assume that all users are located inside a high-rise building as shown in Figure 4.1, and use (xi,yi,zi) to denote the location of user i. The dimensions of the high-rise building, in the shape of a rectangular prism, are [0, xb] × [0, yb] × [0, zb]. Also, let dout,i be the distance between the UAV and indoor user i, let θi be the incident angle that represents the angle between the line of sight path and a unit vector normal to the building wall, and let din,i be the distance between the building wall and indoor user i.

3.2 Outdoor-Indoor Path Loss Models

The Air-to-Ground path loss model presented in [48] is not appropriate when we consider wireless coverage for indoor users, because this model assumes that all

$$L_i = L_F + L_B + L_I = (w \log_{10} d_{out,i} + w \log_{10} f_{Ghz} + g_1)$$
$$+(g_2 + g_3(1 - \cos\theta_i)^2) + (g_4 d_{in,i})$$

users are outdoors and located at 2D points. In this work, we adopt the Outdoor-Indoor path loss model, certified by the ITU [55], for the lower part of the Super High-Frequency band (low-SHF) (450 MHz to 6 GHz). The path loss is given as follows:
where LF is the free space path loss, LB is the building penetration loss, and LI is the indoor loss. In this model, we also have w=20, g1=32.4, g2=14, g3=15,g4=0.5 [55] and fGhz is the carrier frequency.
In [56], the authors clarify the Outdoor-to-Indoor path loss characteristics based on the measurement for 0.8 to 37 GHz frequency band. We adopt this path loss model for the high-SHF operating frequency (over 6 GHz). The path loss is given as follows:

$$L_i = L_F + L_B + L_I = (\alpha_1 + \alpha_2 \log_{10} d_{out,i} + \alpha_3 \log_{10} f_{Ghz}) +$$
$$(\beta_1 + \frac{\beta_2 - \beta_1}{1 + exp(-\beta_3(\theta_i - \beta_4))}) + (\gamma_1 d_{in,i})$$

In this model, we have α_1=31.4, α_2=20, α_3=21.5, β_1=6.8, β_2=21.8, β_3=0.453, β_4=19.7 and γ_1=0.49.

3.3 Problem Formulation of Providing Wireless Coverage Sigle UAV

Consider a transmission between a UAV located at (xUAV, yUAV, zUAV) and an indoor user i located at (xi,yi,zi). The date rate for user i is given by:

$$C_i = Blog_2(1 + \frac{P_{t,i}/L_i}{N})$$

where B is the transmission bandwidth of the UAV, Pt,i is the UAV transmit power to indoor user i, Li is the path loss between the UAV and an indoor user i and N is the noise power. In this work, we do not explicitly model interference, and instead, implicitly model it as noise.

Let us assume that each indoor user has a channel with bandwidth equals B/M, where M is the number of users inside the building and the rate requirement for each user is v. Then the minimum power required to satisfy this rate for each user is given by:

$$\mathrm{P} = \sum_{i=1}^{\mathrm{M}} \left(2\frac{\nu.\mathrm{M}}{\mathrm{B}} - 1\right) \times \mathrm{N} \times L_i$$

Our goal is to find the optimal location of the UAV such that the total transmit power required to satisfy the downlink rate requirement of each indoor user is minimized. The objective function can be represented as:

where P is the UAV total transmit power. Since $(2\frac{v.M}{B} - 1) \times N$ is constant, our problem can be formulated as:

$$\min_{x_{UAV}, y_{UAV}, z_{UAV}} L_{Total} = \sum_{i=1}^{M} L_i$$

$$subject\ to$$

$$x_{min} \leq x_{UAV} \leq x_{max},$$

$$y_{min} \leq y_{UAV} \leq y_{max},$$

$$z_{min} \leq z_{UAV} \leq z_{max},$$

$$L_{Total} \leq L_{max}$$

The first three constraints represent the minimum and maximum allowed values for xUAV, yUAV and zUAV. In the fourth constraint, Lmax is the maximum allowable path loss and equals Pt,max/((2$\frac{v.M}{B}$-1)×N) where Pt,max is the maximum transmit power of UAV.

Finding the optimal placement of UAV is generally difficult because the problem is non-convex. Therefore, in the next subsection, we consider three special cases of practical interest and derive efficient solutions under these cases.

3.4 Problem Formulation of Providing Wireless Coverage Multiple UAV

Providing wireless coverage to High-rise buildings using a single UAV can be impractical, due to the limited transmit power of a UAV. The transmit power required to cover the building is too high. It is in the range of 50 dBm to 65 dBm (see Figures 4.3-4.6), which corresponds to 100-3000 watts. In this section, the UAVs adopt a frequency division multiple access (FDMA) technique to provide wireless coverage for the indoor users in which the total bandwidth B is divided into multiple subchannels, and we allocate one subchannel to each indoor user. Therefore, there is no interference between UAVs. Furthermore, the authors in [61] show that significant power gains are Providing wireless coverage to High-rise buildings using a single UAV can be impractical, due to the limited transmit power of a UAV. The transmit power required to cover the building is too high. It is in the range of 50 dBm to 65 dBm (see Figures 4.3-4.6), which corresponds to 100-3000 watts. In this section, the UAVs adopt a frequency division multiple access (FDMA) technique to provide wireless coverage for the indoor users in which the total bandwidth B is divided into multiple subchannels, and we allocate one subchannel to each indoor user. Therefore, there is no interference between UAVs. Furthermore, the authors in [61] show that significant power gains are:

$$
\begin{aligned}
&\min |k| \\
&\textbf{subject to} \\
&\sum_{j=1}^{|k|} y_{ij} = 1 && \forall i \in m \quad (4.2.a) \\
&\sum_{i=1}^{|m|} (2^{\frac{v.|m|}{B}} - 1).N.L_{ij}.y_{ij} \le P && \forall j \in k \quad (4.2.b) \\
&x_{min} \le x_j \le x_{max} && \forall j \in k \quad (4.2.c) \\
&y_{min} \le y_j \le y_{max} && \forall j \in k \quad (4.2.d) \\
&z_{min} \le z_j \le z_{max} && \forall j \in k \quad (4.2.e)
\end{aligned}
\qquad (4.
$$

where k is the set of UAVs required to provide wireless coverage for indoor users, m is the set of indoor users that requests a wireless coverage, υ is the rate requirement for each user (constant), N is the noise power (constant), B is the transmission bandwidth (constant), Lij is the total path loss between UAV j and user i and P is the maximum transmit power of UAV (constant). We also introduce the binary variable yij that takes the value of 1 if the indoor user i is connected to the UAV j and equals 0 otherwise. The objective is to minimize the number of UAVs that are needed to provide wireless coverage for indoor users. Constraint set (4.2.a) ensures that each indoor user should be connected to one UAV. Constraint set (4.2.b) ensures that the total power consumed by a UAV should not exceed its maximum power consumption limit. Constraints (4.2.c-4.2.e) represent the minimum and maximum allowed values for xj, yj and zj.

4. Simulation Result for a Single UAV

First, we verify our results for the second case, when the locations of indoor users are symmetric across the xy and xz planes, using different operating frequencies, 2GHz for low-SHF band and 15GHz for high-SHF. We assume that each floor contains 20 users. Then we apply the gradient descent (GD) algorithm to find the optimal horizontal point xUAV that minimizes the transmit power required to cover the indoor users.

Vertical width of building y_b	50 meters
Hight of each floor	5 meters
Step size a ”GD algorithm”	0.01
Maximum number of iterations N_{max} ”GD algorithm”	500
The carrier frequency f_{Ghz}, low-SHF	2 GHz
The carrier frequency f_{Ghz}, high-SHF	15 GHz
Number of users in each floor	20 users
(varmin,varmax) ”PSO algorithm”	(0,1000)
$(\kappa,\varphi_1,\varphi_2)$ ”PSO algorithm”	(1,2.05,2.05)

Table 1.1 Parameters in numerical analysis for single UAV.

we find the optimal horizontal points for a building of different heights. In the upper part of the figures, we find the total path loss at different locations (xUAV, 0.5yb, zUAV) and the optimal horizontal point xUAV that results in the minimum total path loss using the GD algorithm. In the lower part of the figures, we show the convergence speed of the GD algorithm. As can be seen from the figures, when the height of the building increases, the optimal horizontal point xUAV increases. This is to compensate for the increased building penetration loss due to an increased incident angle.

After that, we assume that each floor contains 20 users and the locations of these users are uniformly distributed on each floor. When we apply the GD algorithm, the 3D efficient placements and the total costs for 200 meter, 250 meter and 300 meter buildings are (24.7254, 25, 100) (7.8853 ∗ 104), (33.8180, 25, 125) (9.9855 ∗ 104) and (43.1170, 25, 150)(1.2154 ∗ 105), respectively. UAV efficient placement and the convergence speed of the PSO algorithm for different building heights are shown in Figure 4.12. The 3D efficient placements and the total costs for 200 meter, 250 meter and 300 meter buildings are (21.7995, 37.3891, 111.7901) (7.8645 ∗ 104), (32.9212,28.7125,124.0291)(9.9725∗104)and(46.5898, 31.5061 ,143.8588)(1.2117 ∗ 105), respectively. As can be seen from the simulation results in Table 4.3, the PSO algorithm provides better results. It provides total cost less than the cost that the GD algorithm provides by (37dB-208dB). This is because the PSO algorithm is designed for the case in which the locations of indoor users are uniformly distributed in each floor. On the other hand, the GD algorithm is designed for the case in which the locations of indoor users are symmetric across the dimensions of each floor.

5. Simulation Result for a Multiple UAVs

In this section, we verify our results for multiple UAVs scenarios. First, we assume that a building will host a special event (such as a concert, conference, etc.), the dimensions of the building are [0, 20] × [0, 50] × [0, 100]. The organizers of the event reserve all floors higher than 75 meters and they expect that 200 people will attend the event. Due to interference from nearby macro cells, the organizers decide to use UAVs to provide wireless coverage to the indoor users. We assume that 200 indoor users are uniformly distributed in the upper part of the building (higher than 75 meters) and 200 indoor users are uniformly distributed in the lower part (less than 75 meters). Then, we apply the clustering indoor user's algorithm to find the minimum number of UAVs required to cover the indoor users.

Maximum transmit power of UAV (P)	5 watt
Operating frequency (f)	2Ghz
Transmission bandwidth (B)	50M Hz
Rate requirement for each user (υ)	2.2 Mbps
Noise power (N)	-150 dBm
Min and Max allowed values for x_j,$[x_{min}, x_{max}]$	[25,1000]
Min and Max allowed values for y_j, $[y_{min}, y_{max}]$	[0,50]
Min and Max allowed values for z_j, $[z_{min}, z_{max}]$	[0,1000]

Table 1.2 Parameters in numerical analysis for multiple UAVs

The algorithm starts with k = 2 and after it finishes clustering the indoor users, it applies the particle swarm optimization to find the UAV 3D location and UAV transmit power needed to cover each cluster. Then, it checks if the maximum transmit power is sufficient to cover each cluster, if not, the number of clusters k is incremented by one and the problem is solved again. we need 5 UAVs to cover the indoor users. We can notice that an efficient horizontal point xUAV for all UAVs 3D locations is the same xUAV = 25, the minimum allowed value for xUAV , this is because the trade-off disappears when a UAV covers small height of building.

We uniformly split the building into k parts and cover it by k UAVs. As can be seen from the simulation results, we need 9 UAVs to cover the indoor users. The clustering algorithm provides better results, this is because it utilizes the distribution of indoor users to divide them into clusters. On the other hand, the uniformly split method is designed for the case in which the locations of indoor users are uniformly distributed in the building.

6. Conclusion

The research delves into the challenge of minimising the number of UAVs essential for ensuring continuous coverage over a specified area. Recognising the inherent complexity of this task, the study introduces a novel approach to partitioning the coverage graph into cycles originating from a central charging station. This innovative strategy aims to optimise the deployment of UAVs by characterising the minimum number required to cover a cycle. Factors such as charging time, travelling time, and the number of subareas within the cycle are carefully considered in this analysis. Subsequently, an efficient algorithm is developed to address this optimisation problem, offering a practical solution for minimising the UAV resources while maintaining seamless coverage.

The research shifts its focus to the optimal placement of a single UAV to minimise the total transmit power necessary for providing wireless coverage to indoor disaster users. The study highlights the constraints posed by the limited transmit power capacity of UAVs, prompting an investigation into methods for reducing the overall power consumption while ensuring effective coverage for indoor environments. Through the development of a sophisticated algorithm, the research presents a systematic approach to optimising the placement of UAVs and minimising the total transmit power required to serve indoor users efficiently.

In conclusion, this thesis contributes valuable insights and innovative solutions to the field of UAV deployment for coverage optimisation for disaster emergency communication. By exploring the challenges of minimising UAV numbers for continuous coverage and optimising transmit power for indoor wireless communication, this research opens new avenues for enhancing the efficiency and effectiveness of UAV-based systems. The proposed algorithms offer practical tools for addressing these complex optimisation problems, paving the way for advancements in UAV technology and wireless communication networks.

7. Future Works

The research opens several promising avenues for future exploration and development in the field of UAV deployment and wireless communication optimisation. Some potential directions for further research include:

Path Loss Modelling: While existing path loss models are often based on simulation software, future work could benefit from real-world experimentation to better understand the statistical behaviour of path loss. Conducting empirical studies to validate and refine path loss models for both low-altitude and high-altitude platforms can enhance the accuracy and reliability of communication systems deployed using UAVs.

Practical Path Loss Models for Urban Environments: The utilisation of UAVs as aerial relay nodes to maximise ground user throughput often relies on the assumption of free space propagation, which may not hold true in urban settings. Future research efforts could focus on incorporating practical path loss models tailored to urban environments, enabling a more realistic evaluation of UAV-assisted communication systems in complex urban landscapes.

Enhanced UAV Deployment Strategies: Expanding the study on minimising the number of UAVs required for continuous coverage by considering additional factors such as varying energy capacities of UAVs and the utilisation of multiple charging stations can lead to more robust and adaptable deployment strategies. Exploring these realistic scenarios can offer valuable insights into optimising UAV resource allocation and enhancing coverage efficiency.

Lifetime Maximization for Wireless Devices: Extending the investigation into maximising the lifetime of wireless devices to encompass indoor users presents an intriguing research direction. By considering the specific requirements and challenges of indoor environments, future studies can develop tailored strategies to prolong devices lifetime while maintaining reliable wireless connectivity for indoor users.

Multi-Building Indoor Wireless Coverage: Addressing the challenge of providing indoor wireless coverage across multiple buildings introduces a complex and multifaceted scenario that warrants further exploration. Future research can delve into the design and optimisation of UAV-based solutions that cater to the diverse connectivity needs of users spread across multiple indoor spaces, offering enhanced coverage and connectivity solutions.

By pursuing these future research directions, the field stands to benefit from a more comprehensive understanding of UAV deployment challenges and wireless communication optimisation, ultimately leading to the development of innovative solutions that address real-world needs and scenarios.

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