Energy Efficiency and Hover Time Optimization in UAV-Based HetNets

By

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Approval

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Abstract

In this dissertation, we investigate the performance of downlink transmission link in a three-tier HetNet. Our goal here is to enhance the edge capacity of a macro cell by deploying unmanned aerial vehicles (UAVs) as flying base stations and small cells (SCs) for improving the capacity of indoor users in scenarios like temporary hotspot regions or during disaster situations where the terrestrial network is either insufficient or out of service. UAVs are energy-constrained devices with a limited flight time, which makes it vital that we utilize that energy in the most optimum manner. Our approach here is to formulate this as a two layer optimization scheme, where we first optimize the power consumption of each tier for enhancing the system energy efficiency under the minimum QoS requirement, which is followed by optimizing the average hover time of UAVs. We can find the solution to these nonlinear constrained optimization problems by first utilizing the Lagrange multipliers method and then implementing sub-gradient method for obtaining convergence. The results show that through optimal power allocation, the system EE improves significantly in comparison to when maximum power is allocated to ground users. The hover time optimization results in increased flight time of UAVs thus providing service for longer durations.

Dedication

I dedicate this thesis to my parents, Muhammad Ajmal Mughal and Samina Ajmal. They are the most selfless and courageous people I have witnessed in my life. They have been my utter strength and support through each and every phase of my life. I am nothing without them.

Certificate of Originality

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any degree or diploma at NUST SEECS or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at NUST SEECS or elsewhere, is explicitly acknowledged in the thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except for the assistance from others in the project's design and conception or in style, presentation and linguistics which has been acknowledged.

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Acknowledgment

Firstly, I would like to thank the most beneficent and the most merciful, the one and only, the Almighty Allah. Allah has forever blessed me with more than I deserved and ever dreamed of. And it is only by Allah's grace that I have been able to complete my research.

I would then like to express my utter gratefulness to my supervisor Dr. Syed Ali Hassan for giving me the opportunity and the honor to work under his guidance. I thank him for being so patient with me, for guiding me every step of the way with his immense knowledge and for motivating me to complete my research.

And in the end I would like to thank my parents for forever being my support system, I could not have done this without their untiring efforts and prayers.

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Chapter 1

Introduction

Over the past few years, the demand for higher data rates and uninterrupted data communication has radically increased. The number of data users are increasing enormously with each passing year. With the latest research and development in 5th Generation (5G) technology, we appear to be achieving that milestone sooner than expected. Unmanned Aerial Vehicles (UAVs) have become very popular lately. UAVs provide cost-efficient and easy to implement solution for improving data rates of ground users. Small Cells (SCs) are low-powered base stations which provide high data rates for indoor users and to users in a small region. But dense deployment of SCs comes at the cost of increased interference. If a Heterogeneous Network (HetNet) is formed consisting of Macro Base Station (MBS), Unmanned Aerial Vehicles (UAVs) and Small Cells, then optimizing it can result in better system efficiency and extended network coverage [1-3].

1.1 Heterogeneous Networks

With the versatility in data demand, heterogeneous networks can provide better energy efficiency of the system as compared to homogeneous networks. In homogeneous networks, the entire network consists of similar base stations with one tier complexity. This energy can be wasteful where user data demand is minimal. We can make an energy efficient system by exploiting the heterogeneity of multi-tier networks. Low-powered base stations can be deployed where user demand is less and hence improving overall network performance [3] and [6]. The system model defined in this thesis is a three-tier heterogeneous network (HetNet) consisting of macro base station (MBS), unmanned aerial vehicles (UAVs) and small cells (SCs).

1.2 Unmanned Aerial Vehicles

The emerging trend in 5th Generation Networks is Unmanned Aerial Vehicles (UAVs). UAVs are gaining popularity mainly because of their agility, effortless deployment, and ability to make LoS connections with ground users, thus giving better data rates than terrestrial cellular networks [1] and [4]. UAVs have vast applications as they can utilize their ability to provide coverage to users based on their locations by hovering over the area with denser user distribution, hence superseding the performance of terrestrial base stations.

1.2.1 Applications of UAVs

Apart from the extensive applications in navigation, Internet of Things (IoT) and Wireless Sensor Networks (WSN), UAVs have vital applications in providing network coverage during disaster situations and crowded regions when the traditional infrastructure is either not operational or adequate to cater for the needs of all users [1], [2] and [4]. During disaster situations like earthquake, when either the whole communication infrastructure is down or some of the base stations are out of work, then UAVs can provide coverage to users under such scenario. UAVs can form backhaul network in case of severe damage to terrestrial network and they can also work as relay between two base stations. Drones have the advantage of making better LoS connections than MBS or SCs. They can be used to enhance the edge capacity in a macro cell tier. The users on the edge of the cell get lower data rates due to increased path loss and signal attenuation. UAVs can provide on-demand service to users which are in outage. And in hotspot regions where terrestrial network is not enough to accommodate the increased number of users, UAVs can provide economical and reliable service to ground users [1]. In wireless sensor networks (WSN), a reliable and a low latency uplink connection is required for effective transmission of gathered data from sensors to control center. UAVs act as low-powered base stations and they provide better data transmission due to their ability to make LoS connections [7]. Different applications of UAVs are shown in Fig. 1.1.

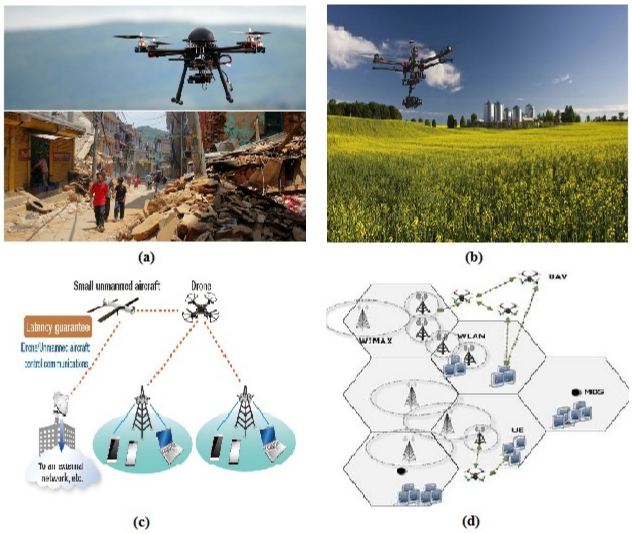

Figure 1.1: Applications of UAVS: (a) UAVs in disaster situations. (b) UAVs in WSNs. (c) UAVs acting as backhaul and relays. (d) UAVs for improving edge capacity in macro cell tier.

1.3 Small Cells

Despite the increase in data demand, the available spectrum is exhausted, and it cannot be further enhanced in efficiency. We need a larger spectrum to cater for the increasing data requirements. But as the frequency increases, the signal propagation decreases. But higher frequency translates to higher data rates. Small cells (SCs) are low-powered base stations having small range and providing higher data rates. SCs are used to enhance and extend the edge capacity of macro cell tier. SCs are used specifically for indoor users [8].

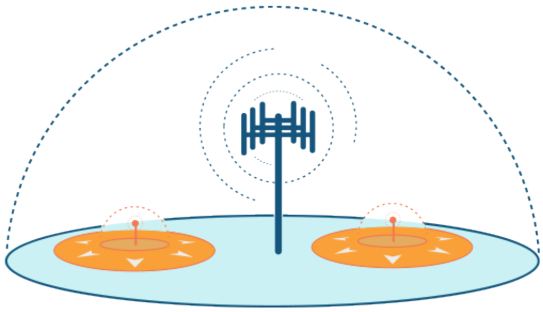

Figure 1.2: Small cells extending coverage of macro cell.

1.4 Challenges in UAV-Based HetNets

Unmanned Aerial Vehicle deployment as a base station has many challenges of its own. In a heterogeneous network, the UAV deployment as a separate tier under macro cell tier poses its own challenges. In a HetNet, managing the overall system energy efficiency, the hover time management of UAVs and the interference caused on all three tiers are some of the few issues [1].

1.5 Motivation

In the last ten years, the number of mobile users has drastically increased, and hence the demand for data. Everything revolving around our lives is connected to internet in some way. The terrestrial networks have a limited bandwidth and capacity for serving the growing number of users. Also, with the increase in high rise buildings and population density, the edge users do not get adequate cell coverage. In a multi-tier system, each added tier can enhance the capacity of terrestrial network. Small cells are there to increase the coverage of indoor users. While UAVs have multiple purposes, they can be deployed on-demand in certain disaster scenarios, in crowded places and to enhance the coverage of edge users. The motivation behind this thesis is to improve the overall system energy efficiency and hover time of UAVs in a three-tier heterogeneous network consisting of macro base station, small cells and UAVs.

1.6 Thesis Organization

The remaining part of the thesis is organized as: In chapter 2 the relevant review regarding Heterogeneous networks, Unmanned aerial vehicles, small cells, EE and hover time of UAVs is discussed. In chapter 3, system model is presented along with the problem formulation. And then later in chapter 3, we present the optimal power allocation schemes for the HetNet and hover time optimization for UAVs. Chapter 4 presents the simulation results and discusses the outcomes. Chapter 5 conclude the thesis along with giving a way forward for the future work in the related area.

Chapter 2

Literature Review

The popularity of unmanned aerial vehicles (UAVs) is increasing due to its vast applications. UAVs have the capability of making better line of sight connections as compared to terrestrial base stations. UAVs can be easily deployed hence can be beneficial to provide network coverage in the case of disaster and emergency information dissemination scenarios. A lot of work has been done this field. UAVs face several key challenges such as 3D deployment of UAVs, Air-to-Ground (A2G) channel modeling, performance analysis, hover time optimization and energy efficient operation of UAVs [1]. In this chapter, a summary of the relevant literature review is presented.

2.1 3D Placement of UAVs

The authors in [9], has taken into consideration the power efficient deployment of UAVs in an all-UAV network. UAVs are deployed in such a way as to minimize the power consumed by the UAVs while satisfying the users' rate requirement. The authors in [10] deploys UAVs in such a way as to maximize the coverage area and service maximum number of users while minimizing the power in an all-UAV network. UAVs are used as flying base stations in this work. The work in [11] focuses on deploying UAVs on need basis in case of crowd scenarios. By creating a heterogeneous network in which UAVs act as flying base stations to augment the network coverage. In [12], UAVs are put on standby on a microcell, and they are flown to the desired location to provide coverage to the macro cell users in case of outage or to improve data requirements. The authors in [13] deals with the 3-D placement of UAVs in order to enhance network capacity of terrestrial networks. UAVs are typically designed for servicing outdoor users. But in [14], UAVs are placed in a manner to provide coverage to indoor users in a high rise building when the terrestrial network is out of service.

2.2 Air-to-Ground Channel Model

The traditional channel modeling for terrestrial networks is not suitable for UAVs, due to factors like mobility, varying altitude and distinctive power constraints. Therefore Air-to-Ground (A2G) channel models are formed for the operation of UAVs. The authors in [15] describe what all factors effect the A2G channel model as shown in figure below. The probability of having line of sight (LoS) and non-line of sight (NLoS) signals depend upon the environment, small-scale and large-scale fading, shadowing, and most importantly height and placement of UAV.

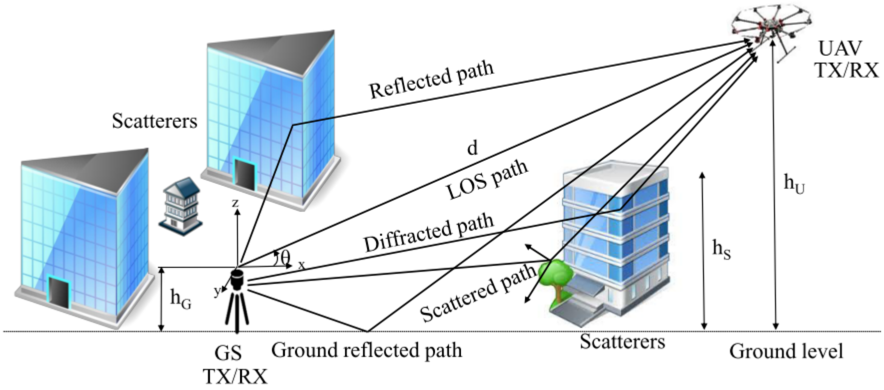

Figure 2.1: Air-to-Ground signal propagation using a UAV.

2.3 UAV Performance

The authors in [16] discuss the performance of UAVs when they are used as flying base stations (FBS). FBS are proven to provide enhanced performance as compared to ultra-dense fixed small base stations. The authors have considered the mobility of users as well as the variation in their data requirement, to get more realistic results. Which hence makes the FBS a far better choice than static base stations. In [17] the authors investigate the effect of offloading user data from ground base stations to UAVs in case of crowded situations and show that the overall data delivery improves this way. In [18-30], the UAVs acting as flying base stations are repositioned so that the spectral efficiency of the network increases. When UAVs are repositioned according to changing user locations, then there are better chances of LoS connections and fewer packet losses.

2.4 UAV Hover Time

In [2], the hover time of UAVs is optimized through efficient cell partitions of UAVs in an all-UAV network. Cells are formed on the basis if user density, so that user fairness is obtained. The area with high user density gets smaller partition and vice versa. This way the UAVs hover on their respective partitions for almost equal times. The work in [19] and [31-40] is very similar to the one in [2]. In this paper, flight time is optimized through optimally partitioning cells of UAVs to ensure load fairness among users.

2.5 Energy Efficiency Analysis in UAV-based Networks

In [7], UAVs are deployed as flying base stations with the purpose of collecting data from the Internet of Things (IoT) devices. This kind of network requires an energy efficient system, so that UAVs can operate for longer durations. The authors in this paper have adopted several techniques to make this an energy efficient system by optimizing the deployment, mobility, trajectory and power of UAVs. Due to optimal placement and mobility of UAVs, the UAVs as well as the IoT devices consume much less power. The authors in [5] have considered a HetNet comprising of three tiers that is macro cell, small base stations (SBSs) and UAVs. Ultra-high frequency (UHF) band is used for macro cell and UAVs, while SBS utilize the millimeter wave (mmWave) band. The number of UAVs and SBSs are fixed. In this paper, the authors have enhanced the energy consumption of the system and power is optimized.

In [19], the system in which UAVs are being used as FBS is made energy efficient by optimizing the trajectory of the UAVs in an all-UAV network [41-50].

To the best of my knowledge, no work has considered energy efficiency and hover time optimization of a multi-tier UAV-based heterogeneous network.

Chapter 3

Implementation

3.1 System Model

Consider downlink transmission in a multi-tier HetNet consisting of k tiers such that $k \epsilon K = \{m,u,s\}$ where m is for an MBS, $u \epsilon \{1,2,...,U\}$ UAVs and $s \epsilon \{1,2,...,S\}$ SCs placed randomly in a geographical area which has N users distributed according to a random distribution. There are a total of M base stations such that $M_k \epsilon M = \{M_m, M_u, M_s\}$ where $k \epsilon \{m,u,s\}$. All three tiers are operating on ultra-high frequency (UHF) band where each tier k shares the same bandwidth B with the other two tiers. The bandwidth B is divided into L subcarriers and exclusive subcarriers are assigned to each user within a tier k, hence no co-tier interference exists but the cross-tier interference is present. The user coordinates are given by (x_n, y_n, z_n) where $n \epsilon \{1,2,...,N\}$. The location of MBS is denoted by (x_m, y_m), while the locations of SCs are denoted by $(x_{s,j}, y_{s,j})$ where $j \epsilon \{1,2,...,S\}$. The UAVs' locations are given by $(x_{u,j}, y_{u,j}, h_{u,j})$, where $h_{u,j}$ represents the altitude of UAV and $j \epsilon \{1,2,...,U\}$.

τ_j represents the hover time of j^{th} UAV base station. Hover time is the time that a UAV consumes while making connections and transmitting data to the users. Optimizing hover time extends the total flight time of UAVs. Each base station has a maximum power of ${P_{max}}^j$ for $j \in \{1,2,...,M_{\mathrm{k}}\}$ where $M_k \in M$.

The path loss equations as given in [3] for n^{th} user associated with j^{th} base station of MBS tier k_m and for n^{th} user associated with j^{th} base station of SC tier k_s are respectively given by

$$
{PL_{n,j}}^{k_m}[dB] = 20log_{10}\Big(\frac{4\pi f_{\mathrm{c}}}{c}\Big) + 10\alpha log_{10}\big(d_1\big) + \Psi \tag{3.1}
$$

$$
{PL_{n,j}}^{k_s}[dB] = 20log_{10}\Big(\frac{4\pi f_{\mathrm{c}}}{c}\Big) + 10\beta log_{10}\big(d_2\big) + \Psi \tag{3.2}
$$

where α and β are the path loss exponents for MBS and SC tiers respectively, f_c is the carrier frequency, and Ψ is the log normal shadowing variable. Whereas d_1 is the distance between n^{th} user and j^{th} BS of tier k_m while d_2 is the distance between n^{th} user and j^{th} BS of tier k_s and are given as $d_1 = \sqrt{\big(x_m \text{ - } x_n\big)^2 + \big(y_m \text{ - } y_n\big)^2}$ and $d_2 = \sqrt{\big(x_{s,j} \text{ - } x_n\big)^2 + \big(y_{s,j} \text{ - } y_n\big)^2}$ respectively.

The path loss equation for UAV tier k_u as given in [2] and [4] for n^{th} user associated with j^{th} BS is

$$
{PL_{n,j}}^{k_u} = \kappa_{\mathrm{o}} d^2\big(P_{\mathrm{LoS},n}\mu_{\mathrm{LoS}} + P_{\mathrm{NLoS},n}\mu_{\mathrm{NLoS}}\big) \tag{3.3}
$$

where $\kappa_{\mathrm{o}} = \left(\frac{4\pi f_{\mathrm{c}}}{c}\right)^2$, μ_{LoS} and μ_{NLoS} are the additional attenuation factors for LoS and NLoS connections, and d is the distance between n^{th} user and

j^{th} BS of tier k_u and is given as $d = \sqrt{\big(x_{u,j} \text{ - } x_n\big)^2 + \big(y_{u,j} \text{ - } y_n\big)^2 + {h_{u,j}}^2}$. The probability of having LoS and NLoS connections depends upon certain factors like elevation angle between user and UAV, the atmospheric effects and the position of UAV with respect to users. The probability of LoS connection is given by

$$P_{\text{LoS},n} = \frac{1}{1 + aexp\big(- b[\theta - a]\big)} \tag{3.4}$$

where a and b are constants to incorporate the atmospheric effects(rural, urban, or dense urban etc.). The angle of elevation θ is given by $\theta = \frac{180}{\pi} \sin^{-1}\left(\frac{h_{u,j}}{d}\right)$. UAV forms better LoS connections when the angle of elevation is 90$^{\text{o}}$, but as the value of θ decreases the probability of LoS connections decreases as well. Also, the probability of NLoS is given as $P_{\text{NLoS}} = 1 - P_{\text{LoS}}$.

Each user associates to a BS of any tier $k \,\epsilon\, K$ based on the maximum received power given as

$$Pr_{n,j}{}^{k}[\ell] = \frac{P_{max}{}^{j}}{PL_{n,j}{}^{k}} \tag{3.5}$$

where $P_{max}{}^{j}$ is the maximum transmit power of any j^{th} BS. The achievable rate between user n using subcarrier ℓ and j^{th} BS of tier $k \,\epsilon\, K = \{k_m,k_u,k_s\}$ is

$$R_{n,j}{}^{k}[\ell] = B_\ell log_2\big(1 + \gamma_{n,j}{}^{k}[\ell] p_{n,j}{}^{k}[\ell]\big) \tag{3.6}$$

where B_ℓ is the bandwidth assigned to each subcarrier. Considering that the total bandwidth that each BS gets is B and the total number of subcarriers available to any BS are L, then $B_\ell = \frac{B}{L}$. The transmit power of user n using subacarrier ℓ associated with j^{th} BS is $p_{n,j}{}^{k}[\ell]$, and $\gamma_{n,j}{}^{k}[\ell]$ is the channel-to-interference and noise ratio which is given as

$$\gamma_{n,j}{}^{k}[\ell] = \frac{\left|h_{n,j}{}^{k}[\ell]\right|^2}{\left(N_\text{o}B_\ell + I_{n,j}{}^{k}[\ell]\right)PL_{n,j}{}^{k}} \tag{3.7}$$

In the above equation, $\left|h_{n,j}{}^{k}[\ell]\right|^2$ is the squared envelope of multipath fading, N_o is the thermal noise power, and $\text{PL}_{n,j}{}^{k}$ is the average path loss between user n and j^{th} BS. $I_{n,j}{}^{k}[\ell]$ is the total cross-tier interference caused on subcarrier ℓ of user n associated with j^{th} BS of tier k which is being shared by a user associated with any other two tiers. The interference caused on subcarrier ℓ is given by

$$I_{i,m}{}^{k_o}[\ell] = \sum_{\substack{k\epsilon K\\ k\neq k_\text{o}}} \sum_{j=1}^{M_k} \sum_{n=1}^{N_k} \sum_{\ell=1}^{L_k} \sigma_{n,j}{}^{k}[\ell] p_{n,j}{}^{k}[\ell] \rho_{n,j}{}^{k}[\ell] \tag{3.8}$$

where $\sigma_{n,j}{}^{k}[\ell] = 1$ if the subcarrier is being shared by any other user, otherwise $\sigma_{n,j}{}^{k}[\ell] = 0$, and $\rho_{n,j}{}^{k}[\ell]$ is given by $\rho_{n,j}{}^{k}[\ell] = \frac{\left|h_{n,j}{}^{k}[\ell]\right|^2}{PL_{n,j}{}^{k}}$. Each user consumes a circuit power equaling to P_c when a connection is established between user n and j^{th} BS. Total system power can be calculated as,

$$P_\text{total} = \sum_{k\epsilon K} \sum_{j=1}^{M_k} \sum_{n=1}^{N_k} \sum_{\ell=1}^{L_k} p_{n,j}{}^{k}[\ell] + (N \times P_\text{c}) \tag{3.9}$$

whereas the system EE is defined as

$$EE = \frac{\sum\limits_{k\epsilon K} \sum\limits_{j=1}^{M_k} \sum\limits_{n=1}^{N_k} \sum\limits_{\ell=1}^{L_k} R_{n,j}{}^{k}[\ell]}{\sum\limits_{k\epsilon K} \sum\limits_{j=1}^{M_k} \sum\limits_{n=1}^{N_k} \sum\limits_{\ell=1}^{L_k} p_{n,j}{}^{k}[\ell] + (N \times P_\text{c})} \tag{3.10}$$

3.2 Problem Formulation

The proposed methodology here is to optimize the power consumption of each tier simultaneously hence forming a sub-optimal system which will lead to the optimization of hover time of UAVs. Optimizing hover time will enable us to provide service to more users and for a longer duration. Power of each tier is optimized so that the system energy efficiency can be increased. Each user n associates to the tier k which reduces the cross-tier interference caused by the other two tiers on user n. The EE of each tier is optimized by putting a constraint on the maximum transmit power ${P_{max}}^j$ of the j^{th} BS, minimum rate requirement R_{min} of user n, and a threshold on the cross-tier interference caused on user n associated with j^{th} BS of tier k caused by the users associated with other tiers. The power of each tier is optimized to form an energy efficient system.

3.2.1 Power Allocation for MBS Tier

The objective equation for solving the EE optimization problem for MBS tier is formulated as

$$\max_{p_{n,j}} EE = \max_{p_{n,j}} \left[\sum_{j=1}^{M_{k_m}} \sum_{n=1}^{N_{k_m}} {R_{n,j}}^{k_m}[\ell] - \Big(\sum_{j=1}^{M_{k_m}} \sum_{n=1}^{N_{k_m}} {p_{n,j}}^{k_m}[\ell] + (N \times P_{\mathrm{c}}) \Big) \right], \quad \forall \ell \tag{3.11}$$

under the constraints

$$\sum_{j=1}^{M_{k_m}} \sum_{n=1}^{N_{k_m}} p_{n,j}{}^{k_m}[\ell] \leq P_{max}{}^{j}, \quad \forall \ell$$
$$R_{n,j}{}^{k_m}[\ell] \geq R_{\min}, \quad \forall n, j \tag{3.12}$$
$$\sum_{\substack{k \epsilon K \\ k \neq k_{\mathrm{m}}}} \sum_{j=1}^{M_k} \sum_{n=1}^{N_k} \sigma_{n,j}{}^{k}[\ell] p_{n,j}{}^{k}[\ell] \rho_{n,j}{}^{k}[\ell] \leq I_{th}[\ell], \quad \forall \ell$$

where the first constraint puts limit on the total transmit power of users associated with j^{th} BS, the second constraint ensures the minimum rate requirement of user n, and the third constraint puts a limit on the interference experienced by the user.

We solve the above optimization problem through the Lagrangian function which is given as

$$\mathcal{L}(p, \boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\phi}) = \sum_{j=1}^{M_{k_m}} \sum_{n=1}^{N_{k_m}} \sum_{\ell=1}^{L_{k_m}} B_{\ell} log_2\big(1+\gamma_{n,j}{}^{k_m}[\ell] p_{n,j}{}^{k_m}[\ell]\big) - \Big(\sum_{j=1}^{M_{k_m}} \sum_{n=1}^{N_{k_m}} \sum_{\ell=1}^{L_{k_m}} p_{n,j}{}^{k_m}[\ell]$$
$$+ (N \times P_{\mathrm{c}}) \Big) + \sum_{j=1}^{M_{k_m}} \sum_{n=1}^{N_{k_m}} \mu_{n,j} \Big(\sum_{\ell=1}^{L_{k_m}} B_{\ell} log_2\big(1+\gamma_{n,j}{}^{k_m}[\ell] p_{n,j}{}^{k_m}[\ell]\big) - R_{\min} \Big) + \sum_{j=1}^{M_{k_m}} \lambda_j \Big(P_{max}{}^{j}$$
$$- \sum_{n=1}^{N_{k_m}} \sum_{\ell=1}^{L_{k_m}} p_{n,j}{}^{k_m}[\ell] \Big) + \sum_{\ell=1}^{L_k} \phi_{\ell} \Big(I_{th}[\ell] - \sum_{\substack{k \epsilon K \\ k \neq k_{\mathrm{m}}}} \sum_{j=1}^{M_k} \sum_{n=1}^{N_k} \sigma_{n,j}{}^{k}[\ell] p_{n,j}{}^{k}[\ell] \rho_{n,j}{}^{k}[\ell] \Big) \tag{3.13}$$

The above Lagrangian function is solved as two sub-problems. Firstly the optimal power is calculated by applying the KKT (Karush-Kahn-Tucker) conditions and then solving the Lagrange multipliers through the sub-gradient method. The partial derivative of the Lagrangian function with respect to the power is given as

$$\frac{\partial \mathcal{L}(p, \boldsymbol{\mu}, \boldsymbol{\lambda}, \boldsymbol{\phi})}{\partial p_{n,j}} = 0, \tag{3.14}$$

which results in the optimal transmit power ${p_{n,j}}^{k_m}[\ell]^*$ for user n of MBS tier.

$${p_{n,j}}^{k_m}[\ell]^* = \left[\frac{(1+\mu_{n,j})B_\ell}{\left[(1+\lambda_j)+\phi_\ell {\rho_{n,j}}^{k}[\ell]\right]\ln 2} - \frac{1}{{\gamma_{n,j}}^{k_m}[\ell]}\right]^+ \tag{3.15}$$

where $[a]^+ = \max(0,a)$. The Lagrange multipliers μ, λ, and ϕ can be computed using sub-gradient method and are given as follows

$$\begin{aligned}
\mu_{n,j}(i+1) &= \left[\mu_{n,j}(i) - c_1\big({R_{n,j}}^{k_m}[\ell] - R_{\min}\big)\right]^+, \\
\lambda_j(i+1) &= \left[\lambda_j(i) - c_2\big({P_{max}}^{j} - \sum_{n=1}^{N_{k_m}}\sum_{\ell=1}^{L_{k_m}} {p_{n,j}}^{k_m}[\ell]\big)\right]^+, \\
\phi_\ell(i+1) &= \left[\phi_\ell(i) - c_3\big(I_{th}[\ell] - \sum_{\substack{k\epsilon K\\ k\neq k_{\mathrm{m}}}}\sum_{j=1}^{M_k}\sum_{n=1}^{N_k} {\sigma_{n,j}}^{k}[\ell]{p_{n,j}}^{k}[\ell]{\rho_{n,j}}^{k}[\ell]\big)\right]^+,
\end{aligned} \tag{3.16}$$

where c_1, c_2, and c_3 are the step sizes for updating Lagrange multipliers until they converge and i is the iteration number.

The algorithm for MBS power allocation scheme is given below:

Algorithm 3.1 Power allocation for MBS tier

Input: $\mu_{n,j}, \lambda_j, \phi_\ell, B_\ell, {\rho_{n,j}}^{k}[\ell], {\gamma_{n,j}}^{k_m}[\ell]$.
Output: ${p_{n,j}}^{k_m}[\ell]$.
  Set $\mu_{n,j} = \lambda_j = \phi_\ell = 0.01,\ \ c_1 = c_2 = c_3 = 0.01,\ \ i = 1,\ \ i_{\max} = 10^6$
  while $\mu_{n,j}$, λ_j, and ϕ_ℓ have not converged or $i \leq i_{\max}$ **do**
    Calculate ${p_{n,j}}^{k}[\ell]$ from (3.15).
    Update $\mu_{n,j}$, λ_j, and ϕ_ℓ from (3.16).
  end while
End

3.2.2 Power Allocation for UAV and SC Tier

The power allocation for UAV and SC tiers is optimized in a similar way as the MBS tier. The optimal transmit power for UAV and SC tier is given as:

$$p_{n,j}{}^{k}[\ell]^{*} = \left[\frac{(1+\mu_{n,j})B_{\ell}}{\left[(1+\lambda_j)+\phi_{\ell}\rho_{n,j}{}^{k}[\ell]\right]\ln 2} - \frac{1}{\gamma_{n,j}{}^{k}[\ell]}\right]^{+} \tag{3.17}$$

where $k \epsilon \{k_u,k_s\}$.

3.2.3 UAV Hover Time Optimization

A UAV has finite source of energy, which elevates the need to optimize its battery usage so that it can service the users for longer duration. Hence it becomes vital to optimize the hover time of UAVs. Hover time of a UAV is the time it takes to associate with the users through control signaling and then transmitting data. The hover time of a j^{th} UAV is represented by τ_j, where

$$\tau_j = \sum_{n=1}^{N_{k_u}} \sum_{\ell=1}^{L_{k_u}} T_{n,j}{}^{k_u}[\ell] + N_j t_c. \tag{3.18}$$

In the above equation, t_c is the control time of user n and its a constant value for all users. But the total control time of a UAV depends upon the number of users N_j associated with j^{th} UAV. $T_{n,j}{}^{k_u}[\ell]$ is the data transmission time of user n associated with j^{th} UAV. The data transmission time of user n is related to the rate as

$$R_{n,j}{}^{k_u}[\ell] = \frac{\beta_{n,j}{}^{k_u}[\ell]}{T_{n,j}{}^{k_u}[\ell]}, \tag{3.19}$$

where ${\beta_{n,j}}^{k_u}[\ell]$ is the data requirement of user n in bits. The achievable rate of user n using subcarrier ℓ and associated with j^{th} BS of tier k_u is

$$ {R_{n,j}}^{k_u}[\ell] = B_\ell log_2\big(1 + {\gamma_{n,j}}^{k_u}[\ell]{p_{n,j}}^{k_u}[\ell]\big) \tag{3.20} $$

From equation (3.19) and (3.20) we get

$$ {p_{n,j}}^{k_u}[\ell] = \frac{2^{\frac{{\beta_{n,j}}^{k_u}[\ell]}{B_\ell {T_{n,j}}^{k_u}[\ell]}} - 1}{{\gamma_{n,j}}^{k_u}[\ell]} \tag{3.21} $$

The objective equation for solving hover time optimization problem is formulated as

$$ \max_{T_{n,j}} EE = \max_{T_{n,j}} \left[\sum_{j=1}^{M_{k_u}} \sum_{n=1}^{N_{k_u}} \frac{{\beta_{n,j}}^{k_u}[\ell]}{{T_{n,j}}^{k_u}[\ell]} - \sum_{j=1}^{M_{k_u}} \sum_{n=1}^{N_{k_u}} \left(\frac{2^{\frac{{\beta_{n,j}}^{k_u}[\ell]}{B_\ell {T_{n,j}}^{k_u}[\ell]}} - 1}{{\gamma_{n,j}}^{k_u}[\ell]} \right) \right], \quad \forall \ell \tag{3.22} $$

under the constraints

$$ \begin{aligned} &{\beta_{n,j}}^{k_u}[\ell]{T_{n,j}}^{k_u}[\ell] \geq T_{\min}, \quad \forall n, j, \ell \\ &\sum_{n=1}^{N_{k_u}} \sum_{\ell=1}^{L_{k_u}} {T_{n,j}}^{k_u}[\ell] \leq \tau_j - T_{c,j}, \quad \forall j \end{aligned} \tag{3.23} $$

where first constraints determines transmission time based on the minimum rate and load of user, while the second constraint ensures that total data transmission time does not exceed maximum hover time.

The Lagrangian function of the above optimization problem is given as

$$\mathcal{L}(T,\boldsymbol{\mu},\boldsymbol{\lambda}) = \sum_{j=1}^{M_{k_u}}\sum_{n=1}^{N_{k_u}}\sum_{\ell=1}^{L_{k_u}} \frac{\beta_{n,j}{}^{k_u}[\ell]}{T_{n,j}{}^{k_u}[\ell]} - \sum_{j=1}^{M_{k_u}}\sum_{n=1}^{N_{k_u}}\sum_{\ell=1}^{L_{k_u}} \left(\frac{2^{\frac{\beta_{n,j}{}^{k_u}[\ell]}{B_\ell T_{n,j}{}^{k_u}[\ell]}} - 1}{\gamma_{n,j}{}^{k_u}[\ell]}\right) + \sum_{j=1}^{M_{k_u}}\sum_{n=1}^{N_{k_u}} \mu_{n,j} \left(\frac{\beta_{n,j}{}^{k_u}[\ell]}{T_{n,j}{}^{k_u}[\ell]} - T_{\min}\right) + \sum_{j=1}^{M_{k_u}} \lambda_j \left(\left(\tau_j - T_{c,j}\right) - \sum_{n=1}^{N_{k_u}}\sum_{\ell=1}^{L_{k_u}} T_{n,j}{}^{k_u}[\ell]\right) \tag{3.24}$$

This kind of dual-optimization problem is solved by first applying the KKT conditions to the above Lagrangian function and then utilizing the sub-gradient method to obtain the Lagrange multipliers.

$$\frac{\partial \mathcal{L}(T,\boldsymbol{\mu},\boldsymbol{\lambda})}{\partial T_{n,j}} = 0 \tag{3.25}$$

Simplifying (3.25) will give us,

$$\frac{\beta_{n,j}{}^{k_u}[\ell]}{\left(T_{n,j}{}^{k_u}[\ell]\right)^2}\left[\frac{\ln(2).2^{\frac{\beta_{n,j}{}^{k_u}[\ell]}{B_\ell T_{n,j}{}^{k_u}[\ell]}}}{B_\ell \gamma_{n,j}{}^{k_u}[\ell]} - \left(1+\mu_{n,j}\right)\right] - \lambda_j = 0 \tag{3.26}$$

Equation (3.26) is a nonlinear equation and it has no direct solution, hence we solve the equation through numerical methods to obtain the optimal hover time for UAVs. The Lagrange multipliers μ and λ are updated using the sub-gradient method as given below

$$\begin{aligned} \mu_{n,j}(i+1) &= \left[\mu_{n,j}(i) - c_1\left(\frac{\beta_{n,j}{}^{k_u}[\ell]}{T_{n,j}{}^{k_u}[\ell]} - T_{\min}\right)\right]^+, \\ \lambda_j(i+1) &= \left[\lambda_j(i) - c_2\left(\left(\tau_j - T_{c,j}\right) - \sum_{n=1}^{N_{k_u}}\sum_{\ell=1}^{L_{k_u}} T_{n,j}{}^{k_u}[\ell]\right)\right]^+, \end{aligned} \tag{3.27}$$

where c_1 and c_2 are step size and i is the iteration number.

Chapter 4

Simulation Results

In this chapter, the simulation results for the energy efficiency analysis of a three-tier HetNet along with hover time enhancement of UAVs are discussed.

Consider a 1000m x 1000m rectangular region where N ground users are distributed randomly over the area. A macro base station is located at the center of region with U number of UAVs and S number of SCs located at random locations. The bandwidth B given to each tier is 20 MHz and each band is divided into 64 subcarriers. The maximum transmit power for MBS is 45 dBm, and the maximum transmit power for UAVs and SCs is 30 and 27 dBm respectively. The minimum rate requirement of a user is 0.25 Mbps and the interference threshold is set to be 10^{-14} W. Each user has a load of 10 Mb and the maximum hover time of each UAV is 30 minutes. The path loss model parameters are tabulated in Table 4.1.

We have analyzed how the energy efficiency of a HetNet changes when the number of UAVs in the system are increased and how to optimize the hover time of those UAVs for even better performance of the network.

Table 4.1: Simulation Parameters

Parameter	**Description**	**Value**
f_c	Carrier frequency	2.4 GHz
N_o	Thermal noise power	-174 dBm/Hz
α	Path loss exponent for MBS	2.6
β	Path loss exponent for SC	2.5
ψ	Log normal shadowing	4 dB
μ_{LoS}	Additional path loss by LoS connection	1.6
μ_{NLoS}	Additional path loss by NLoS connection	23
a,b	Dense urban environment constants	12.08, 0.11

Fig. 4.1 shows the distribution of users and base stations on a 3-D plane, where users are associated to their respected BS based on the criterion of maximum received power. All UAVs have same height and as the transmit power of MBS is highest among other BSs of the system, most of the users associate with MBS.

Fig. 4.2 reveals that when the number of UAVs increase in our three-tier HetNet, then the proposed optimal power allocation scheme results in an increased system EE as compared to when maximum power is allocated to each ground user. System power consumption is lower in case of optimal power allocation which contributes towards a higher EE. When the number of UAVs increases, the users associated with each UAV decreases, which enables the UAVs to make better LoS connections with their associated users resulting in increased data rates. As more UAVs are inserted in the network, the edge capacity of the macrocell enhances resulting in lesser users in outage, hence better system EE.

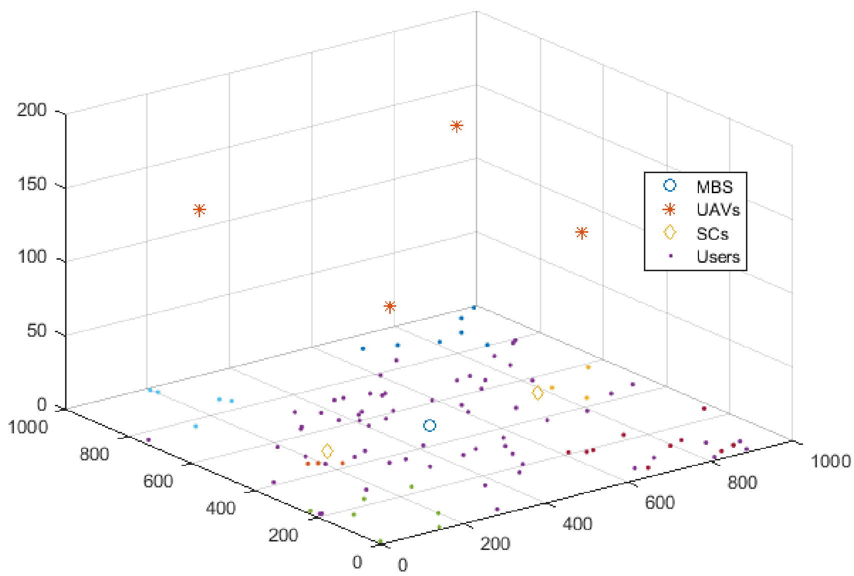

Figure 4.1: User distribution in a three-tier HetNet.

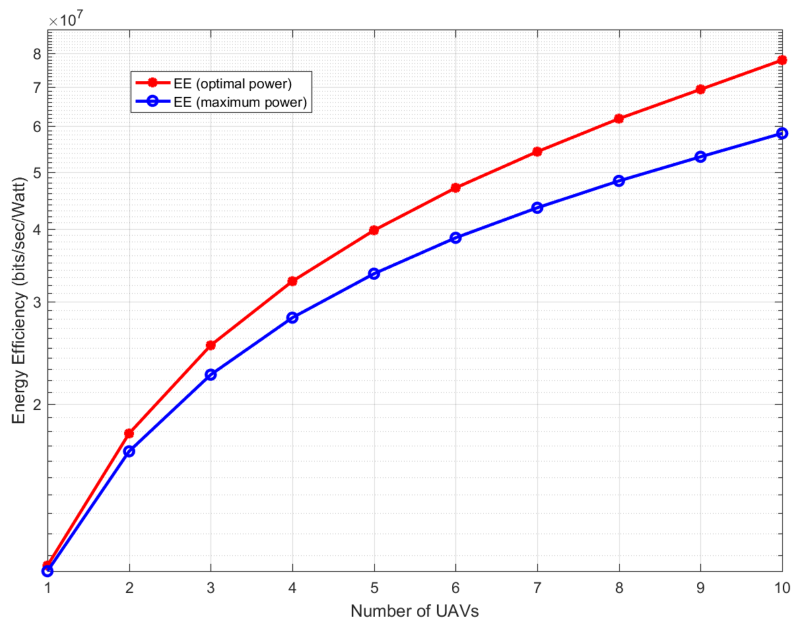

Figure 4.2: System energy efficiency with varying number of UAVs.

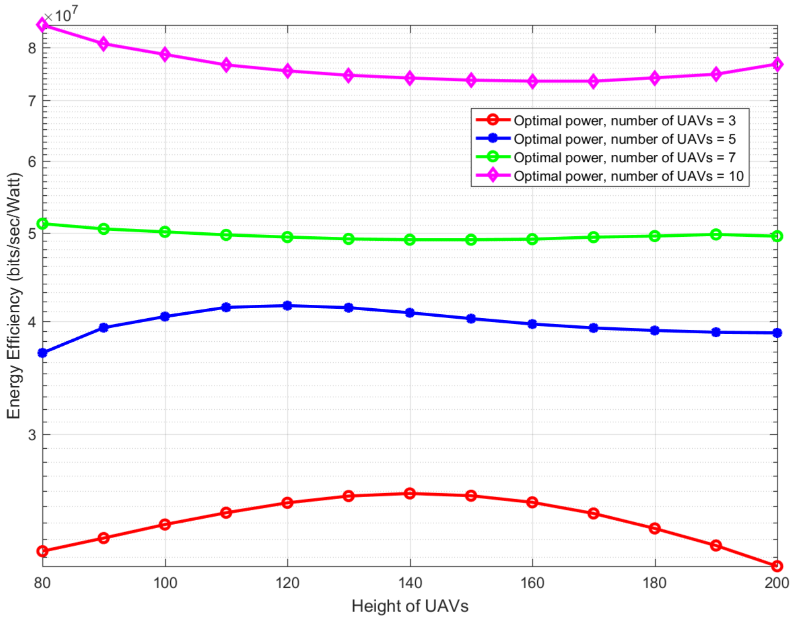

Figure 4.3: System energy efficiency with varying UAV heights for UAVs = 3,5,7 and 10.

Fig. 4.3 shows that how the change in height of UAVs affects the system EE. We can observe that for lower number of UAVs in the network, system EE is maximum for moderate heights between 120m and 140m. This is due to the fact that when number of UAVs is less, then the users associated per UAV are higher than the users associated per UAV for higher number of UAVs. So in this case, a moderate height is suitable. So at lower heights when users are scattered, the probability of LoS connections decreases. But at higher heights, the probability of LoS connections increases and so does free space path loss. When there are 10 UAVs in the network, then system EE is maximum for lower heights like 80m. As users are not much scattered so it gives rise to higher LoS connection probability resulting in increased data rates and enhanced EE.

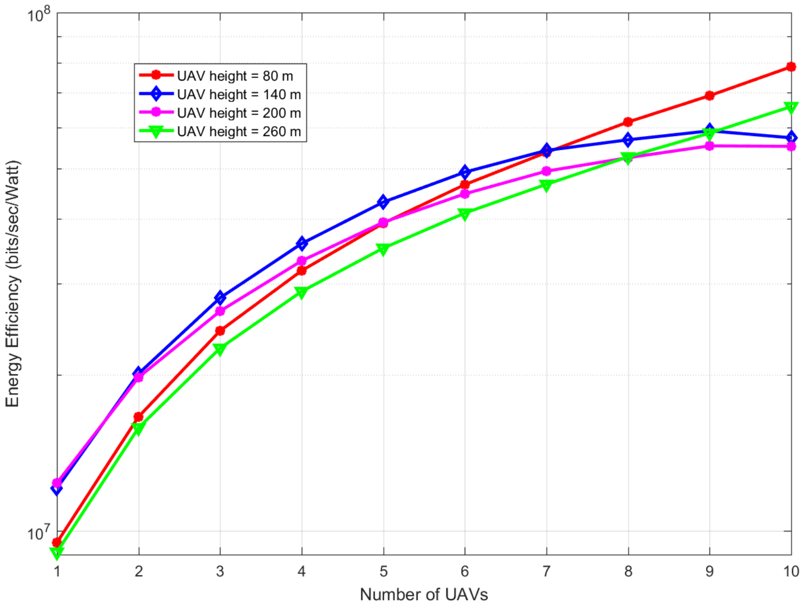

Figure 4.4: System energy efficiency with varying number of UAVs for UAV heights = 80, 140, 200 and 260 m.

We have chosen 140m as the optimal height for all UAVs in our simulations, which can be observed from Fig. 4.4. The figure shows that how the system EE changes for different heights of UAVs as the number of UAVs increases in the network. Till the number of UAVs is 7 in the network, the height of 140m outperforms all other heights and gives the maximum system EE. But as the number of UAVs increases even more, the users associated per UAV decrease and then lower heights are more beneficial. Less scattered associated users of a UAV makes it easier to have better LoS connections at lower heights. UAVs are inserted in the network in case of user densification and increase in user outages at the edge of the cell. This analysis with varying number of UAVs helps us to adjust the system parameters according to our requirements.

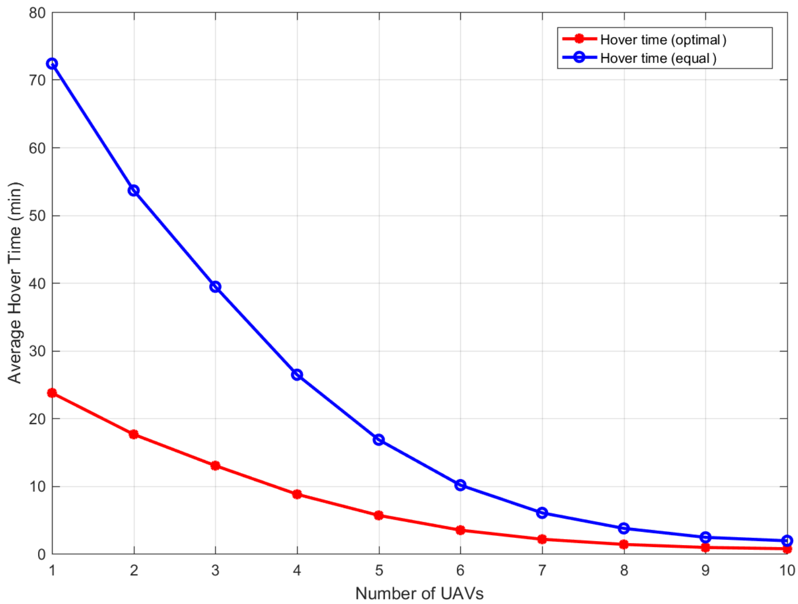

Figure 4.5: Average hover time of UAVs with varying number of UAVs.

Hover time of a UAV is the time which it takes to serve the ground users. As UAVs are battery powered so their energy source is limited, hence it is essential to utilize that energy in the most optimal manner. Fig. 4.5 shows how the average hover time of UAVs changes with varying number of UAVs. It can be observed that the time it takes for a UAV to serve its users when equal time is allocated to the users is significantly higher than the time it takes with optimal hover time allocation. As the number of UAVs increase, fewer users get served by each UAV. And due to optimal hover time allocation, data rates of users increases resulting in quicker data transmission time, and hence UAV has to hover for shorter duration.

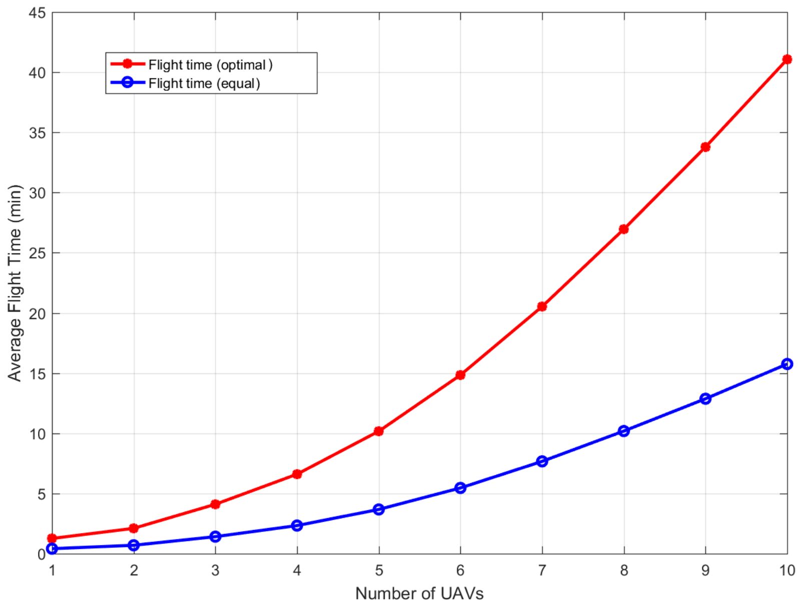

Figure 4.6: Average flight time of UAVs with varying number of UAVs.

Flight time of UAV is the total time that a UAV takes to serve the users. UAVs have maximum flight time of 30 mins, but we can observe in Fig. 4.6 that the flight time has significantly increased in the case of optimal hover time allocation of ground users. When the number of users associated with a UAV increases, then the energy of UAV dissipate rapidly due to performing additional control signaling and data transmissions. As we increase the number of UAVs in the network, the average flight time of UAVs increases due to reduction in the user associations per UAV. We can service ground users for longer durations in the disaster scenarios or crowded regions if we keep on increasing the UAV density.

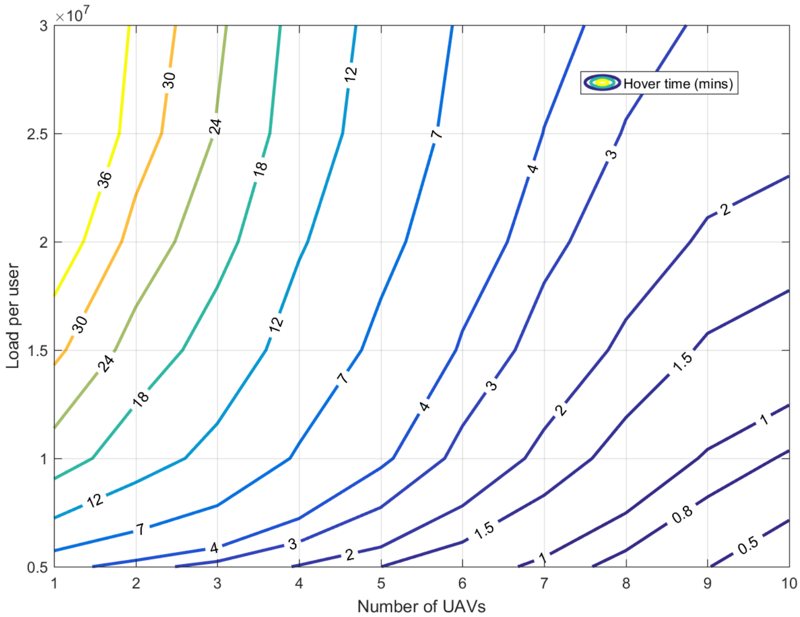

Figure 4.7: Average hover time of UAVs with varying load of users and number of UAVs.

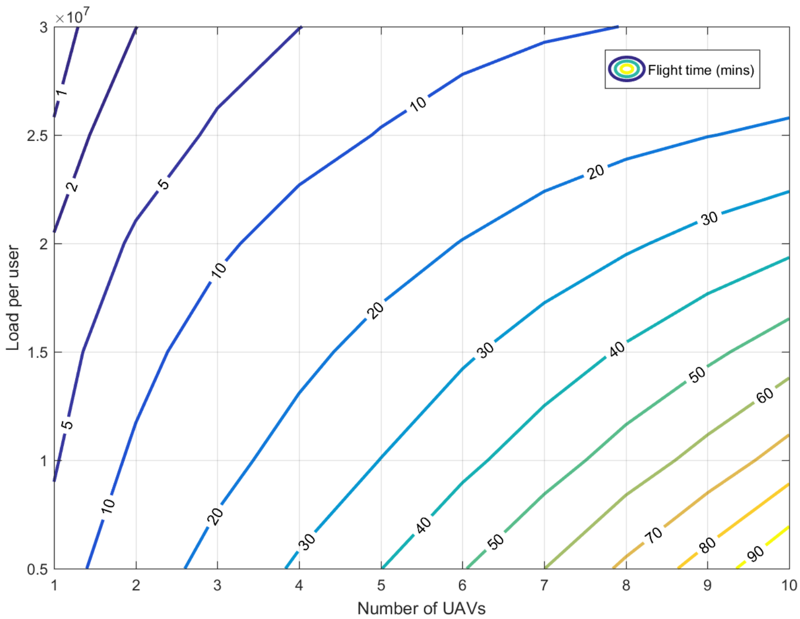

Figure 4.8: Average flight time of UAVs with varying load of users and number of UAVs.

In our simulations, each user has a fixed load requirement of 10 Mb. In Fig. 4.7 we analyze how the changes in load requirement of each user affects the average hover time of UAVs when number of UAVs are varied. When the data demands of a user increase, then UAV will have to hover for longer duration to serve that user. But for the same data demands, if we increase the number of UAVs, then the average hover time decreases. The energy of a single UAV servicing 20 users with load requirement of 20 Mb each will dissipate quickly as compared to 2 UAVs each servicing 10 users. When the load is shared among UAVs, then average hover time decreases significantly.

While in Fig. 4.8 effects on average flight time of UAVs is observed under the variation of user load requirement and number of UAVs in the network. As discussed earlier, flight time is the total time that a UAV can serve the users. When load of each user increases, then the UAV will have to hover for longer duration to serve the users, hence the average flight time of UAVs will decrease, as hovering for longer durations will consume the energy quickly. But if we cannot compromise on our load requirement of user and to maintain a certain flight time of UAVs, then we will have to increase the number of UAVs in the network.

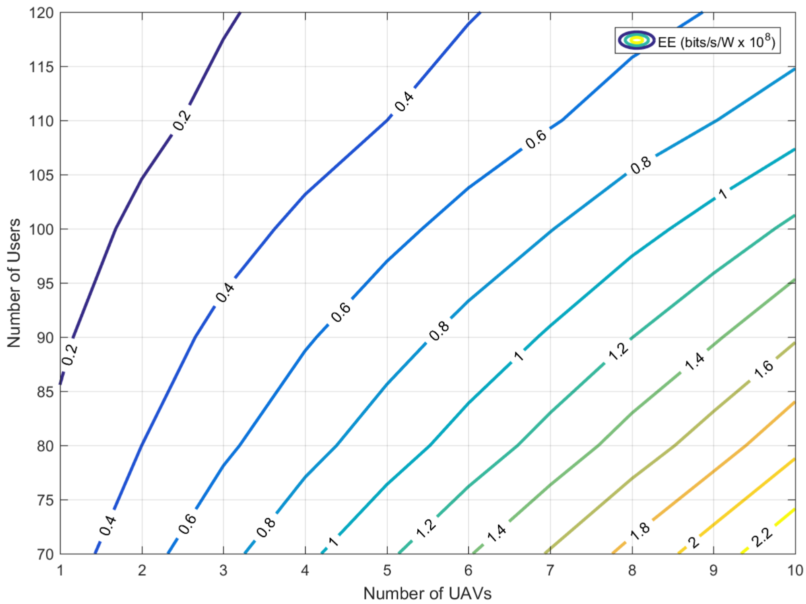

Figure 4.9: System EE with varying number of users and UAVs.

Fig. 4.9 shows the effect of varying number of users and UAVs on system EE. We can observe that when the user density is lower, then the system EE increases. For fewer users, power share for each user increases, and this results in higher data rates. If the user density increase, then to have better system EE, we will have to increase the number of UAVs in the network. System EE drastically decrease if users are increased and there are few UAVs in the network. For situations like providing coverage in hotspot regions like stadiums or arenas, when number of users go beyond the coverage capacity of MBS, then to enhance the system EE and provide coverage to the added users, we will have to place more UAVs in the network.

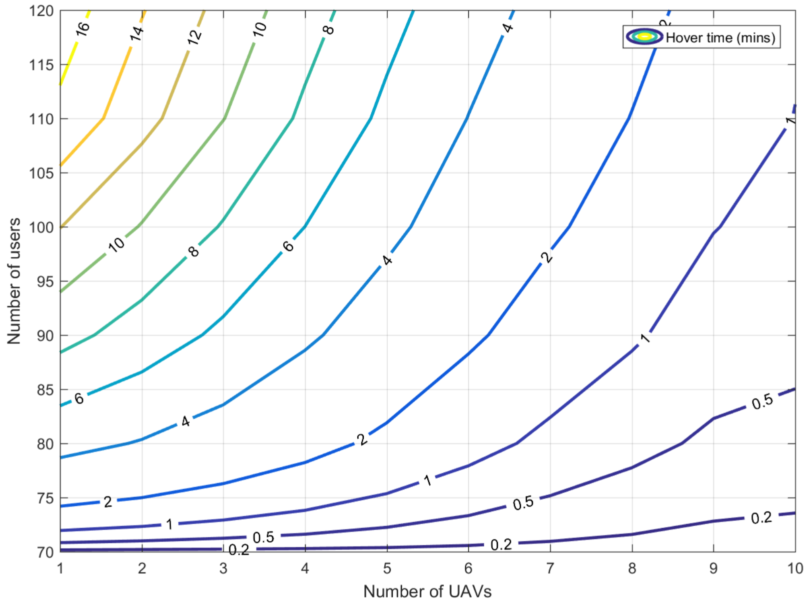

Figure 4.10: Average hover time of UAVs with varying number of users and UAVs.

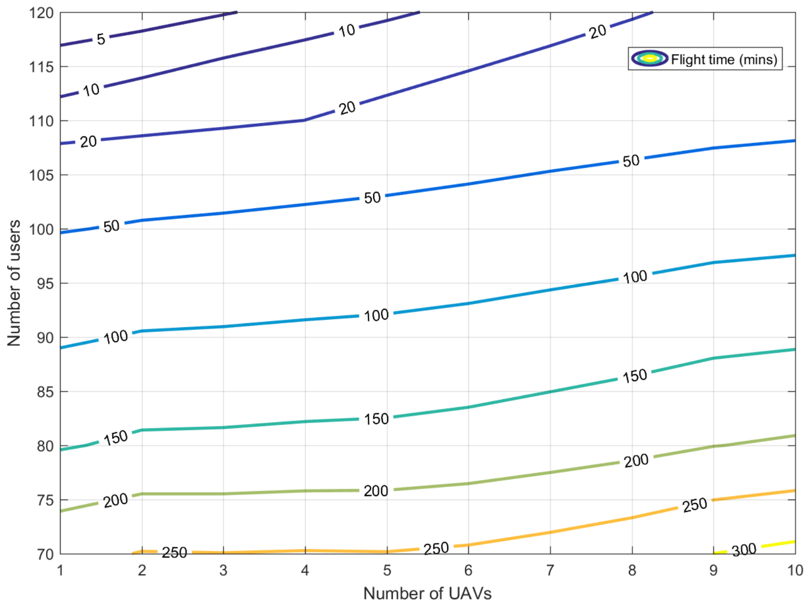

Figure 4.11: Average flight time of UAVs with varying number of users and UAVs.

Hover time of a UAV is dependent on the number of users associated with the UAV. With each additional user, the control signaling time as well data transmission time increases. Fig. 4.10 shows how the change in user density affects the average hover time of UAVs with varying number of UAVs in the network. It is evident from the figure above that as the number of users increase, then the users associated with each UAV increase as well, which gives rise to increase in data transmission time and hence UAV will have to hover for longer duration to service the ground users and its energy will dissipate quickly. If we have disaster scenarios where we want UAVs to provide coverage for longer durations then we will need lower hover time and depending on the number of users, we can adjust the UAV density.

Fig. 4.11 shows that how change in user density affects the average flight time for varying number of UAVs. As discussed above, increasing the number of users depletes the energy quickly and hence UAVs will have to hover for longer duration and perform additional control signaling, which means that UAVs' flight time will decrease drastically. But if we have to serve the additional users for longer durations, then we will have to place more UAVs for higher average flight time and hence increase the service span.

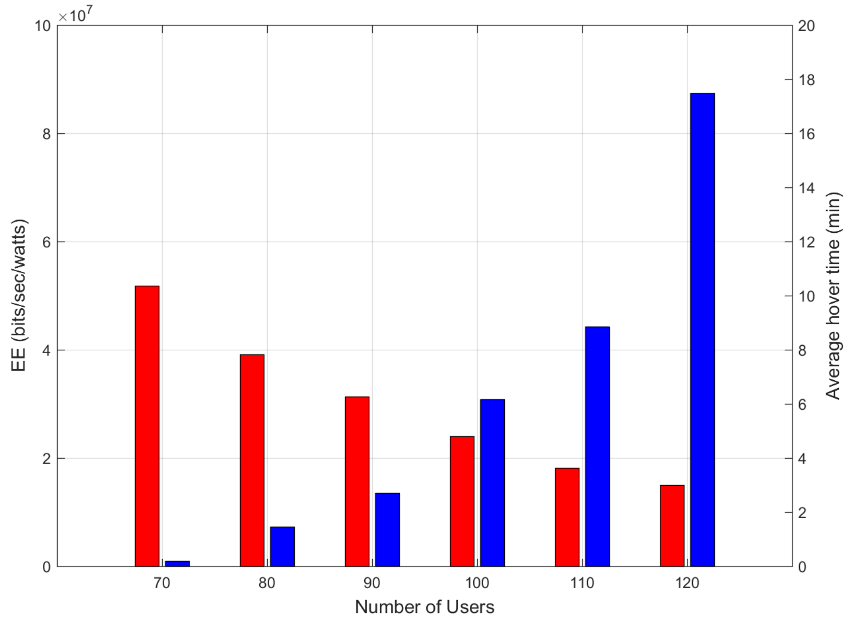

Figure 4.12: System EE vs average hover time of UAVs with varying number of users for UAV = 3.

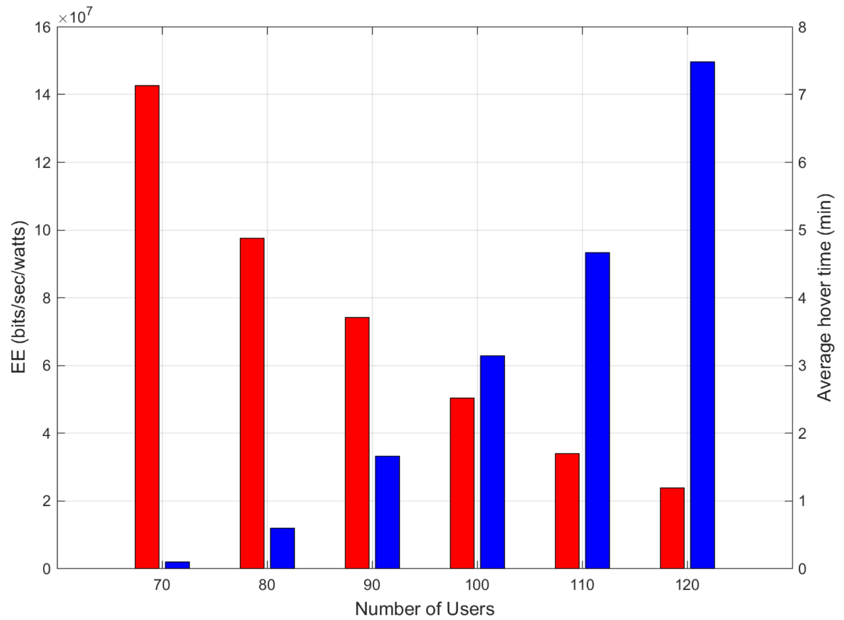

Figure 4.13: System EE vs average hover time of UAVs with varying number of users for UAV = 5.

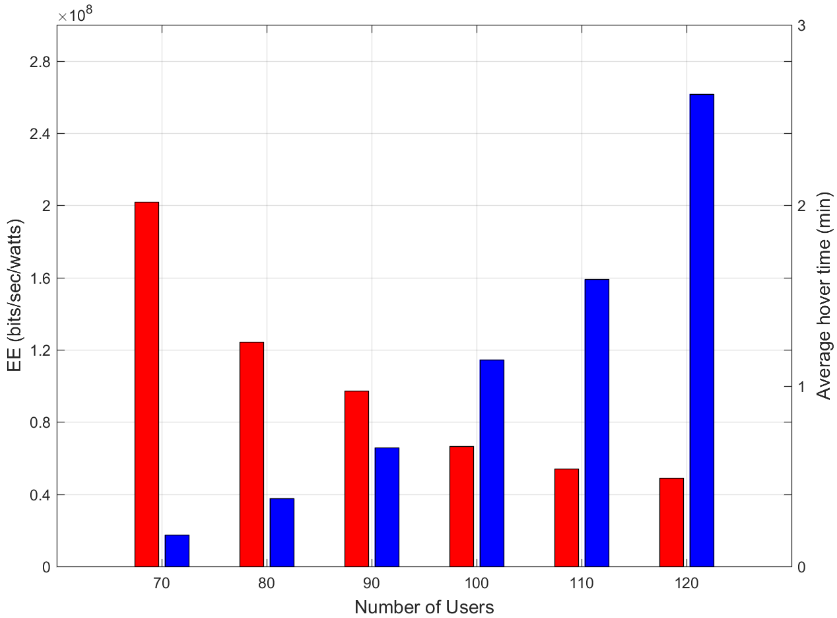

Figure 4.14: System EE vs average hover time of UAVs with varying number of users for UAV = 8.

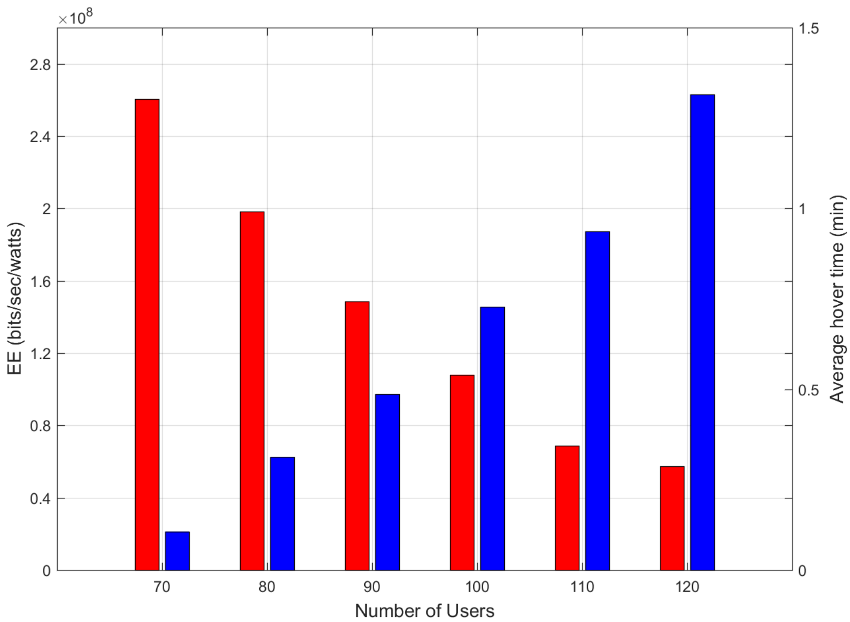

Figure 4.15: System EE vs average hover time of UAVs with varying number of users for UAV = 10.

The goal of this research was to enhance the edge capacity of an MBS in case of scenarios like crowded public gatherings or during an emergency situation to provide coverage for users which cannot be served by the terrestrial network. And while doing so, utilizing the available resources to their maximum potential and conserve the energy of the system. In Fig. 4.12, we have plotted system EE and average hover time of UAVs for different user densities, while the number of UAVs is fixed at 3. We can see that as number of users are increasing, the system EE starts decreasing and average hover time of UAVs is increasing. As the resources are same so added users come at the cost of degrading the system. In Fig. 4.13, we have UAVs fixed at 5. Here we can observe that addition of more UAVs in the network have significantly improved the efficiency of the network even with the additional user load. In Fig. 4.14 and 4.15, we have 8 and 10 UAVs in the network respectively. Comparing these figures can help us determine that if we want to have the energy efficiency above a certain level while also requiring the UAVs to service the users for longer durations, then how much resources to utilize.

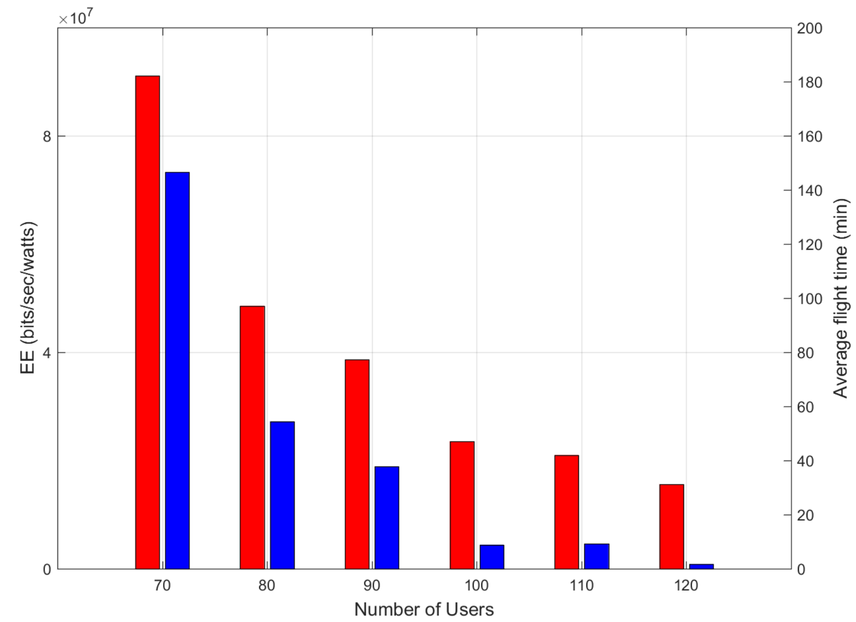

Figure 4.16: System EE vs average flight time of UAVs with varying number of users for UAV = 3.

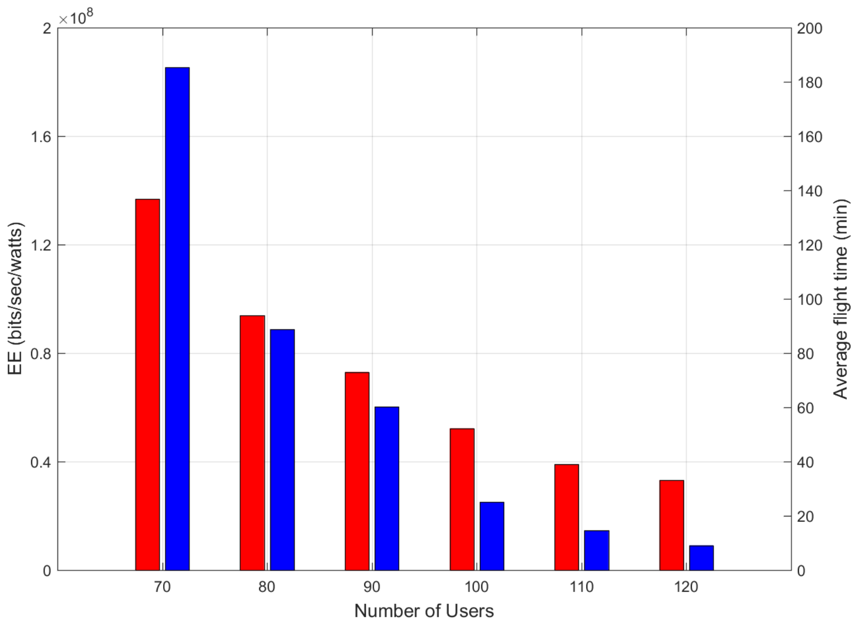

Figure 4.17: System EE vs average flight time of UAVs with varying number of users for UAV = 5.

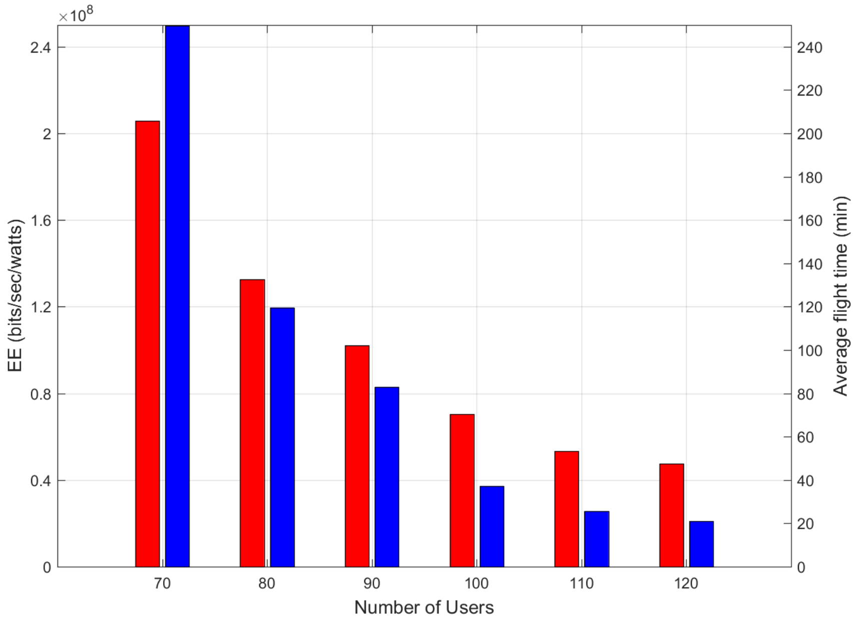

Figure 4.18: System EE vs average flight time of UAVs with varying number of users for UAV = 8.

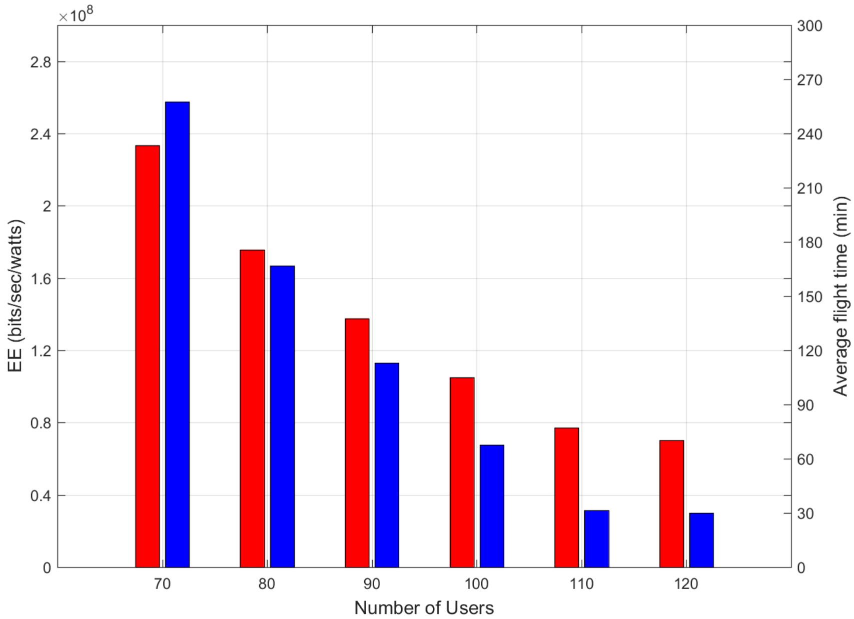

Figure 4.19: System EE vs average flight time of UAVs with varying number of users for UAV = 10.

The results in Fig. 4.16, Fig. 4.17, Fig. 4.18 and Fig. 4.19 helps us evaluate the pattern between system EE and average flight time of UAVs when number of users are varied. All the three tiers are utilizing the same bandwidth, hence cross tier interference occurs and can affect the system EE. As number of users increase, we can observe that system EE starts to drop. But with the increase in users, load on each UAV increases as well, which results in consuming the UAV energy faster and hence we get a lower flight time. In situations like earthquakes or tsunamis, when we have to provide service to users who are disconnected from terrestrial network, then we want to cover them for longer durations. In such cases, our requirement is to have higher average flight time while connecting as many users as we can afford as per our resources, hence we increase the number of UAVs to provide coverage to such areas and for longer durations as evident from the results above. From Fig. 4.16 and Fig. 4.19, we can observe that when number of users are maximum, then the average flight time goes from 3 mins to 30 mins when UAVs are 3 and 10 respectively, which is a significant increase. With the help of results obtained, we can adjust our resources according to the requirement of the network.

Chapter 5

Conclusions and Future Work

With the increase in mobile users and data demands, it has become challenging to satisfy users with the available terrestrial framework. In this research we have formulated a heterogeneous network consisting of UAVs and SCs to enhance the capacity of a macro cell. We have presented a two layer scheme to form an energy efficient system which consists of firstly optimizing the power consumption of each tier and then optimizing the hover time of UAVs. This way we can conserve the energy of the system and utilize it in the most optimum way. We formulated the optimization scheme in the chapter 3 of this dissertation, in which we defined the Lagrangian multipliers method and sub-gradient method to achieve the optimal power for each user and the optimal hover time for UAVs. The results show a significant enhancement in the system EE and the flight time of UAVs. This is particularly beneficial in the cases of temporary hotspot regions and emergency scenarios where we are more concerned with connectivity for longer durations rather than high data rates.

5.1 Furture Work

- In our work, we have not considered a data driven bandwidth allocation that is to allocate bandwidth according to user's data requirements. We have allocated equal bandwidth to each user irrespective of their data needs.

- Secondly, for hover time optimization, we have considered load requirement of each user to be the same. We have not taken into consideration that each user could have different data requirements, like one user could only be web browsing while the other one could be watching a 4K video.

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