Czech Technical University in Prague

Faculty of Electrical Engineering

BACHELOR THESIS

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Czech Technical University in Prague

Faculty of Electrical Engineering

Department of Telecommunication Engineering

Exploitation of unmanned aerial vehicles in mobile networks

Study program: Communications, Multimedia, Electronics
Branch of study: Communication and Electronics

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ČESKÉ VYSOKÉ UČENÍ TECHNICKÉ V PRAZE

ZADÁNÍ BAKALÁŘSKÉ PRÁCE

I. OSOBNÍ A STUDIJNÍ ÚDAJE

Příjmení: **Lystovshchyk** Jméno: **Yevhen** Osobní číslo: **425985**

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Studijní program: **Komunikace, multimédia a elektronika**

Studijní obor: **Komunikace a elektronika**

II. ÚDAJE K BAKALÁŘSKÉ PRÁCI

Název bakalářské práce:

Využití bezpilotních letounů pro mobilní sítě

Název bakalářské práce anglicky:

Exploitation of unmanned aerial vehicles in mobile networks

Pokyny pro vypracování:

Seznamte se s možnostmi využití bezpilotních letounů pro využití v mobilních sítích. Nastudujte si genetické algoritmy a jejich využití pro optimalizaci pozice bezpilotního letounu a asociaci uživatelů k základnovým stanicím. Na základě existujících řešení navrhněte algoritmus pro společnou optimalizaci pozice bezpilotního letounu a asociaci uživatelů k základnovým stanicím. Navržené řešení vyhodnoťte pomocí simulací v prostředí MATLAB.

Seznam doporučené literatury:

[1] B. Galkin, J. Kibilda, L.A. DaSilva, "Deployment of UAV-mounted access points according to spatial user locations in two-tier cellular networks", Wireless Days (WD), 2016. IEEE, 2016.
[2] R. I. Bor-Yaliniz, A. El-Keyi, H. Yanikomeroglu, "Efficient 3-D placement of an aerial base station in next generation cellular networks", 2016 IEEE International Conference on Communications (ICC). IEEE, 2016.

Jméno a pracoviště vedoucí(ho) bakalářské práce:

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Jméno a pracoviště druhé(ho) vedoucí(ho) nebo konzultanta(ky) bakalářské práce:

Datum zadání bakalářské práce: **17.02.2017** Termín odevzdání bakalářské práce: **26.05.2017**

Platnost zadání bakalářské práce: **30.09.2018**

Podpis vedoucí(ho) práce Podpis vedoucí(ho) ústavu/katedry Podpis děkana(ky)

III. PŘEVZETÍ ZADÁNÍ

Student bere na vědomí, že je povinen vypracovat bakalářskou práci samostatně, bez cizí pomoci, s výjimkou poskytnutých konzultací.
Seznam použité literatury, jiných pramenů a jmen konzultantů je třeba uvést v bakalářské práci.

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Datum převzetí zadání Podpis studenta

I hereby declare that this bachelor thesis is completely my own work and that I used only the cited sources in accordance with the Methodical instruction about observance of ethical principles of preparation of university final projects.

Prague, May 26, 2017

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Signature

Abstract

Ever increasing demands of mobile users on mobile networks lead to an ultra-dense deployment of base stations. Nevertheless, this ultra-dense deployment may not be always cost efficient since the eNB may be underutilized most of the time. Therefore, to provide a solution with higher efficiency unmanned aerial vehicles with eNB functionalities become an interesting option.

In this thesis, exploitation of unmanned aerial vehicles as a flying base stations is considered. However, with deployment of flying base stations, their optimal positions have to be calculated as well, as association of user with base stations. Therefore, in this thesis we propose a solution based on genetic algorithm to maximize network throughput while guaranteeing minimal throughput to all users. The proposed solution is compared to the existing algorithms by simulations.

Key words: 5G, UAV, mobile networks, genetic algorithm.

Anotace

Zvyšující se nároky uživatelů na mobilní sítě dnes vedou k nasazení velkého množství základnových stanic. Nicméně toto řešení není vždy efektivní z pohledu nákladů a samotného vytížení základnových stanic. Tudíž pro zlepšení efektivity využití základnových stanic se nabízí možnost použití bezpilotních letounů, rozšířených o komunikační rozhraní.

V této práci je popsána možnost využití bezpilotních letadel, která slouží jako létající základnové stanice. Dále je navržen algoritmus pro určení optimální polohy těchto létajících základnových stanic a výběr obsluhujících základnových stanic pro uživatel. Navržené řešení je založeno na genetických algoritmech a zaručuje všem uživatelům alespoň minimální komunikační kapacitu. Navržené řešení je porovnáno s existujícími pomocí simulací.

Klíčová slova: 5G, bezpilotní letouny, mobilní sítě, genetické algoritmy.

Contents

List of Figures

List of tables

List of Acronyms

4G	Fourth Generation
5G	Fifth Generation
AI	Artificial Intelligence
AWGN	Adaptive White Gaussian Noise
BBU	Baseband Unit
BS	Base Station
CDF	Cumulative Distribution Function
CN	Core Network
EA	Evolutionary Algorithm
eNB	Ultra-dense Base Station
EPC	Evolved Packet Core
FlyBS	Flying Base Station
FlyRAN	Flying Radio Access Network
FlyRRH	Flying Remote Radio Head
GA	Genetic Algorithm
IoT	Internet of Things
M2M	Machine to Machine Communication
MTC	Machine Type Communication
RAN	Radio Access Network
SINR	Signal to Interference and Noise Ratio
UAV	Unmanned Aerial Vehicles
UE	User Equipment
VLC	Visible Light Communication

1. Introduction

Mobile networks have changed a lot throughout the years since their first deployment. It all started with analog transmissions and evolved into a complex, high-capacity systems that support dozens of services (texting, internet access, mms, etc.) in addition to regular voice communication. Basically, development of mobile networks is divided into generations lasting approximately 8-10 years. We are now living in the era of fourth generation (4G) mobile networks and heading towards fifth generation (5G) of mobile networks, which are expected to be deployed around 2020 [1].

Ongoing research and development of mobile networks is necessary due to ever increasing traffic from mobile users. That is why mobile networks of future generations should be able to handle big amount of data. Moreover, mobile networks have to be able to process the data created not only by people, but also generated by machines, known as Machine Type Communication (MTC). The upcoming mobile networks also have to be highly dynamic – that means being able to handle traffic with different priorities and traffic shapes. One of the solutions to handle the mentioned requirements on mobile networks is the ultra-dense base station (eNB) deployment, especially with deployment of small cells with smaller areas of coverage which limit interference [2]

However, the ultra-dense deployment of fixed eNBs may sometimes not be efficient in term of cost, because most of eNBs are underutilized during large portions of time. An interesting option to avoid deployment of underutilized eNBs can be seen in deployment of Unmanned Aerial Vehicles (UAVs) with eNB capabilities. Exploitation of the UAVs is on steep increase as they are being used in rescue operations, delivery or filming. The UAVs are mainly represented by drones, balloons, planes, airships, etc. Besides, implementation of the UAVs into the communication systems is not complicated and can be efficient in not densely populated areas to provide connectivity, i.e areas of temporary growing number of users or for the places where constructing a full network infrastructure would be cost-ineffective [3]. Benefits of deployment of the UAVs are also supported by a performance evaluation in [4], where it is shown that a single UAV can replace up to 10 eNBs in a case of temporal growing number of users. However, there is a significant challenge with deployment of this mobile eNBs to find the best position of the UAVs for providing sufficient quality of service as needed. In case of multiple eNBs it is also necessary to do association of devices, i.e. which users should be served by which eNB.

In this thesis, we propose an algorithm for positioning of UAVs and association of users in mobile networks. The proposed algorithm exploits Genetic Algorithm (GA) for positioning of the UAVs and handles resource allocation algorithm based on water-filling algorithm. The proposed algorithm provides minimal throughput to every user while maximizing network throughput.

The rest of the thesis is composed of the following parts. In the next section, State of the Art solutions for the positioning of UAVs and association of users are described. In

Section 3. mobile networks of 4^{th} generation, development towards 5^{th} mobile networks and implementation of UAVs into mobile networks is provided. In Section 4., Genetic Algorithms, are described. This is followed by description of the proposal. In Section 6. system model, simulation parameters and compared algorithms are described. In Section 7. performance evaluation is done. In the last chapter conclusion and future work of this thesis is provided.

2. Related work

This thesis provides insight for using of UAVs as a flying base stations in mobile networks. As there is existing work in this area, related work for exploitation of UAVs in mobile networks is described in this chapter.

Authors of paper [4] suggest using UAVs enhanced with eNB capabilities for self-organizing Flying Radio Access Network (FlyRAN). It basically means that UAVs enhanced by the eNB functionalities, so called Flying Base Stations (FlyBSs) are positioned automatically in real time, according to requirements of the mobile network. For current mobile networks, only fixed BSs are used, that means that for supplying of mobile users in time, with same level of service as possible with FlyBS, multiple BSs are needed [4]. In this paper, the authors propose to position UAV to center of gravity of communication requirements and show theoretical capability of a mobile network with UAVs performing a role of flying BS to provide a sufficient level of service. The results show that exploitation of UAVs in mobile networks is cost and energy efficient. Nevertheless, problems concerning association of devices are not considered. Usage of multiple UAVs scenario is not considered, as well as guaranteeing at least minimal throughput for every user.

In the paper [5], the authors propose cluster analysis algorithms for deploying a set of flying BSs to maximize quality of service of the users. It is shown that UAVs are capable of positioning themselves automatically, following their proposal. For device association k-means clustering method is used.

In [6] a problem of 3-D placement of FlyBS is discussed. It is observed that characteristic of air-to-ground channel is highly dependent on position of a FlyBS (both horizontal and vertical) which leads to a conclusion that positioning of FlyBS plays the most important part for maximizing the quality of service.

In work [7] analysis of usage of small unmanned aerial vehicles (SUAVs) is made. It is shown that SUAVs can perform in different scenarios like coverage of rural areas, or vice versa, assisting fixed base stations in densely populated areas or place with complicated relieve.

In [8] it is proposed to use UAVs for offloading traffic of neighboring cells. It is shown that UAV equipped with cellular technology is capable of resolving temporary overload od traffic in some cells. Moreover, it is considered to be more efficient in terms of cost rather than deploying ground base stations.

Authors of work [10] suggest using a fast deploying mobile networks for rescue operations. It is considered that they are able to operate in wide frequency spectrum in order to be able to initialize connection to any type of mobile phone. Main idea is to be able to allocate position of person who is in danger very fast in order to provide help as soon as possible.

3. Mobile networks

Current 4G mobile networks are all IP based, meaning that all communication is done via IP packets and thus no circuit switching is done compared to previous generations. The 4G mobile networks provide latency in tenths of milliseconds while enabling throughput of hundreds of Mbit/s [7]. The architecture of the 4G mobile networks is depicted in Figure 1. It consists of Core Network (CN) and Radio Access network (RAN). In 4G CN is denoted as Evolved Packet Core (EPC) and provides functionalities such as call control, location control, handover management, data routing, etc. The RAN or Evolved UTRAN (E-UTRAN) provides radio connectivity, radio transmission control and radio resource control among other functionalities for the User Equipments (UEs).

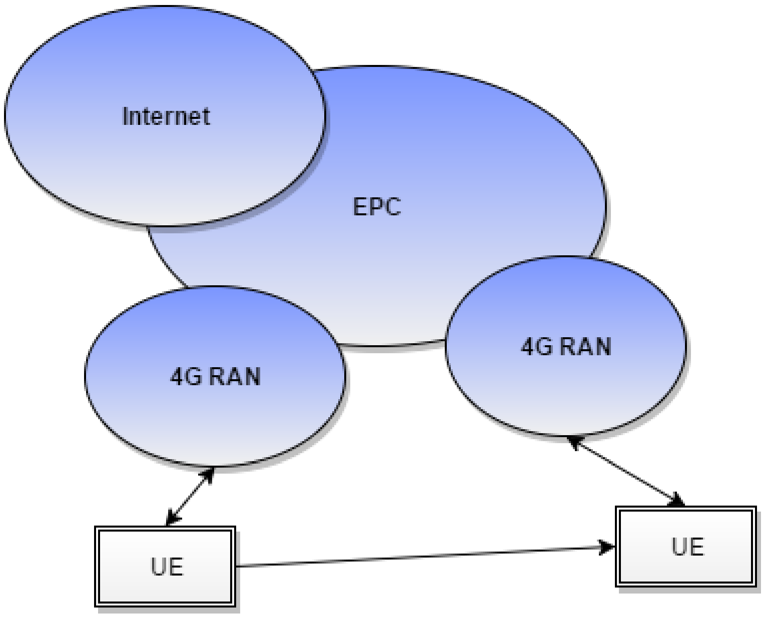


Figure 1. 4G network architecture.

Nevertheless, ever increasing demands of mobile users on mobile networks lead to development fifth generation (5G) mobile networks. The 5G technologies include all types of advanced features, such as internet of things (IoT), machine to machine communication (M2M), etc. Also, big attention is given to cloud services and cloud computation that can improve network capabilities a lot [11].

Another crucial point of modern mobile networks is to perform in a wide range of scenarios and support different types of devices. In order to meet these requirements it should be highly flexible and scalable. Future development of mobile networks also implies usage of ultra-dense base stations deployment [12]. In parallel with humans, a big amount of traffic will be generated by different autonomous machines, devices, sensors, etc. It may cause a so-called fluctuation of traffic that may lead to the situation, when some BSs will be not utilized entirely at some periods. In order to resolve this issue, UAVs may be use.

4. UAVs in the mobile networks

A constant growth of data demand in wireless traffic results the need of implemented new technologies and solutions. Mobile networks of future generations are predicted to rely more on low-power and short-range access point – picocells or eNBs. They are considered to provide better quality of service to the user. Nevertheless, deployment of such cell consumes manpower, time and money. Therefore, an opportunity to exploit UAVs with eNB capabilities arises [6].

Nowadays technical progress allows us to create different kinds of UAVs that meet most of requirements for deployment in mobile networks (flight time, payload carry capability, amount of energy that can be supplied from drone, etc.). The UAVs can be used as FlyBSs by adding communication hardware to provide connectivity for hardly accessible areas or provide a temporary coverage for at a specific location. A crucial point is that this system should work automatically and should be able to self-organize a network on a given location. For example, a crowd of people may require a higher throughput and FlyBS can search and move to the position where it will satisfy the needs of users while complying with constraints on flying and communication. Even when the crowd will move to another spot, the FlyBS will follow it automatically, as depicted in Figure 2a. A crowd of users is being provided connectivity via FlyBS and this crowd is being followed by the FlyBS as shown in Figure 2b. [4].

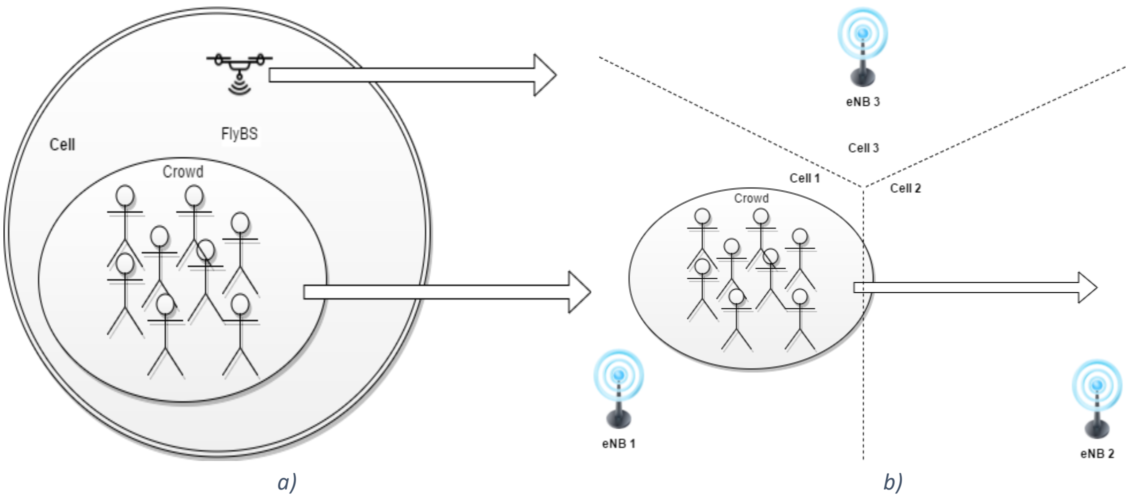


Figure 2. Usage of UAV(a) and fixed eNBs (b) to supply connection to crowd.

The FlyBSs have to be connected to the operator's EPC. This can be achieved by a wireless fronthaul as shown in Figure 3. The FlyBS can be either relaying on communication traffic of an eNB by sharing communication bandwidth between wireless fronthaul and wireless connectivity of the users, or it can act as a Remote Radio Head (RHH) where it has most of the eNB functionalities, while others as provided by a so-called baseband unit (BBU) [4]. Due to the sharing of communication bandwidth, FlyRRH is seen as more interesting solution. Since the FlyBS will be closer to the users, exploitation of mmwaves or even Visible Light Communication (VLC) for increasing communication throughput is possible. This, however puts high requirements on the Wireless fronthaul as data transmitted over this interface will be of a huge amount [4]. However, in this thesis we assume wireless fronthaul of unlimited capacity to show the gain from joint UAV positioning and UEs' association.

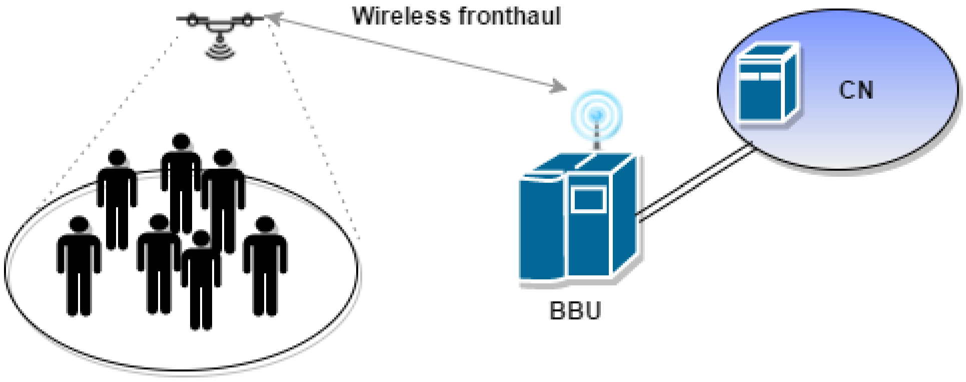


Figure 3. Architecture of mobile network with FlyRAN support.

5. Genetic algorithms

In mobile communication, it is necessary for network to be able to perform self-optimization. It means an ability to adjust network parameters in order to adapt to changes in the environment automatically [13]. The reasons for changing environment may occur due to users mobility or traffic pattern changes. These reasons lead to the need of self-optimization of the mobile networks. One of the approaches for performing self-optimization is Stochastic optimization – a method that creates and uses random variables in order to converge to an optimal solution. Note that since the optimization process if stochastic, global optimum do not have to be reached. An example of stochastic optimization are GAs, which are in this thesis exploited for optimization of UAVs' position and UEs' association.

5.1. Optimization by Genetic Algorithms

The GAs are adaptive heuristic search algorithms that are based on idea of natural selection and genetics for solving optimization problems. They represent an intelligent exploitation of a random search used to solve optimization problems. Though GAs are based on stochastic optimization, they are not random themselves. This is due to exploitation of historical information to lead the search towards the global optimum of a given search space. The GAs are considered to belong to the group of artificial intelligence (AI) algorithms [14].

The GA algorithm process, as shown in Figure 4, starts with process of *Initialization*, which creates initial set of solutions, or *population*. The initial population can be either random or pre-processed. During random initialization, the solutions are generated in a random manner. That means that at the beginning the algorithm relies on pure "luck", by distributing the initial population over the whole search space. On the other hand, pre-processed initialization requires heuristic routines in order to produce initial population with higher probability of converging to the global optimum. However, due to additional need of pre-processing the optimization time and complexity increases, as well as the requirements on data for the pre-processing. Population is a set of individuals, where each individual is one possible solution. Each individual in population has its own fitness level, in other words, how well it satisfies the objective function which is to be either maximized or minimized.

After the generation of the initial population the GA algorithm initializes *selection* process, that crosses out a set of worst solutions, according to their fitness level. Individuals with higher fitness level are more likely to be selected then the ones of smaller level. This may lead to convergence to a solution which is sub-optimal due to selection of the fittest solutions which may be a solution of a local optimum.

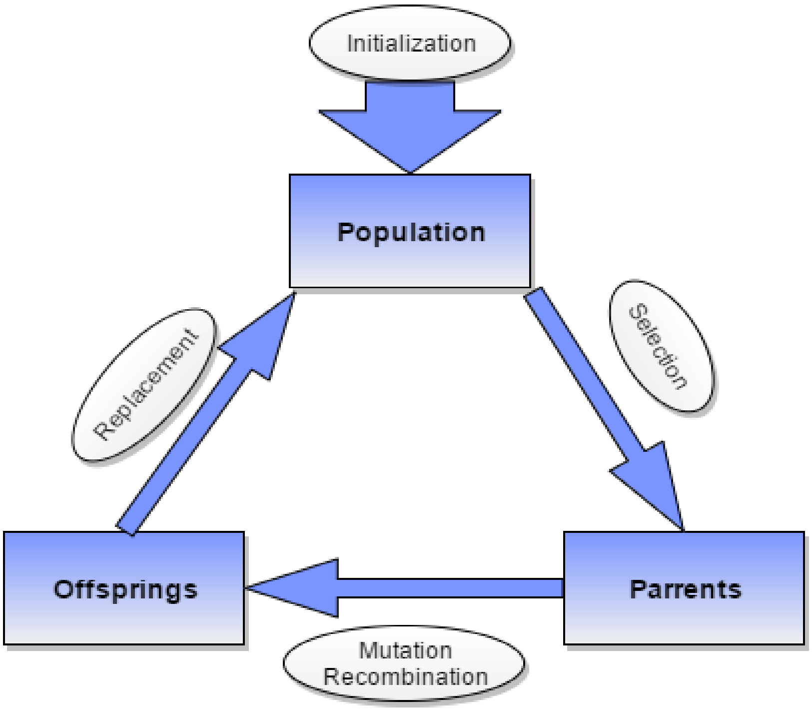


Figure 4. Evolutionary Algorithm cycle.

To avoid convergence to the local optimum, selection process can be realized by Roulette wheel selection. Idea, behind this selection is that each solution has a probability to be selected by the roulette wheel. This probability is dependent on how good the solution is comparatively to other ones (Figure 5).

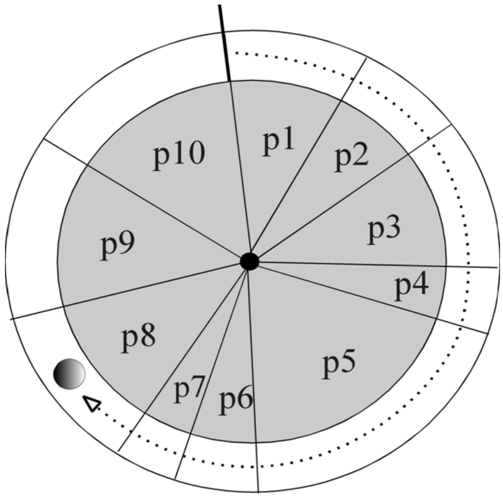


Figure 5. Roulette wheel selection principle

This probability can be shown mathematically as:

$$P_i = \frac{f_i}{\sum_{j=1}^{n} f_j},$$

where *P* is probability of an individual to be selected, *i* is an index of the considered solution, *n* is population size, *f* denotes fitness of the solution. According to formula the probability of selection of individual is dependent on the ratio between fitness of a considered individual and total fitness of the whole population. Besides roulette wheel selection there also exist other methods:

- Tournament Selection.
- Stochastic Universal Sampling.
- Reminder Stochastic Sampling.

The selected set of solutions is now labeled as *parents*, from who *offspring* is generated by *Crossover* and *Mutation* processes.

The idea of *Crossover* is based on a probability that by proper mixing of two solutions, the resulting solution will be better than the original ones (Figure 6). Main goal of this operator is to create a diversity of solutions and improve exploration of search space, i.e. avoid converging to the local optimum.

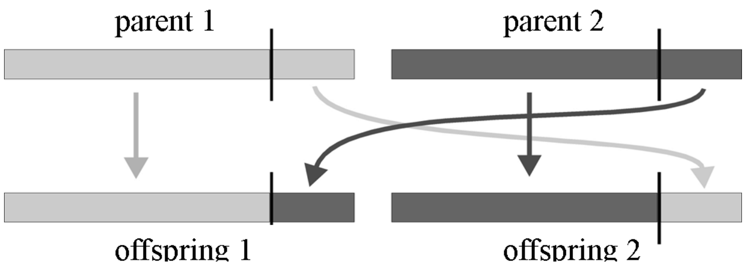


Figure 6. Crossover operator

Mutation operator can make some minor change of a specific solution by modifying a part of a solution (chromosome) to generate more diverse population as shown in Figure 7. Important feature of this operator is preservation of population diversity and reducing probability of losing of some important piece of information.

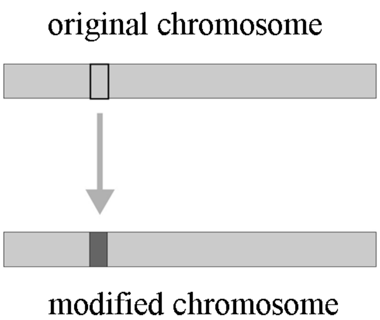


Figure 7. Mutation operator

The last phase of the GA is *Replacement* strategy. During this phase a new population that will be used in the nest loop is formed. It defines the percentage of the population that will be substituted by a newly generated offspring. There also can be extreme cases of this phase:

- **Generational**: the whole population is renewed in each generation (loop);
- **Steady**: only a small portion is substituted each generation.

5.2. Benefits of Genetic algorithms

One of the main advantages of the GAs is that they are very robust and can be used in wide range of scenarios. Besides, it is easy to exploit them as in general only the function for evaluation of the fitness of the solution have to be created.

On the other hand, the disadvantage of the GAs is that it cannot be guaranteed to find global optimum. Similarly to other artificial intelligence techniques, this method cannot assure constant optimization response time. Even tuning all parameters of the GAs (mutation, crossover rate) poses a challenge.

But some of the disadvantages can be minimized or even eliminated by optimization methods that help the GAs produce better results.

5.3. Complexity

Basically, the complexity of GAs cannot be found out precisely. Each run of the algorithm with the same settings and input data consume different time and power. This is mainly because of the origin of the GAs in stochastic optimization. It means that in one run the population or the offspring that is formed, may be closer to global maximum, than in the next run. As a result, in the first case the solution will converge faster and with lower need of resources. Compared to greedy algorithms which consider every possible solution and have a large time and space complexity, the GAs have much lower time and space complexity.

Generally, in the GAs the total size of population remains constant because most unfitting individuals are discarded and later substituted by newly generated population, but so-called “near-optimal” solutions are always taken into account due to crossover and mutation operators. The influence of crossover and mutation on fitness can be observed much better if both crossover and mutation have optimal parameters for the particular application of the algorithm [16]. The complexity analysis of GA means to get the answer whether this method provides advantage or disadvantage in order to solve a particular task over all other methods [14].

6. Joint positioning and association

In this chapter, an algorithm for optimization of the UAVs' position and association of users to available base stations including the UAVs is proposed. Main idea is to provide the highest possible total throughput in order to satisfy all users in particular area. It is achieved by finding the best coordinates for the UAVs. For this reason, the GA is used. Each individual of the population is represented by coordinates of the UAV. As was mentioned earlier, individuals are selected and sorted by their fitness level. In our case fitness level is total throughput of the solution. Finding the best solution is performed by selection process of the final population by means of maximizing Signal to Interference and Noise Ratio (SINR). In other words, solution with the highest total throughput value will be selected. Nevertheless, selecting the solution with the highest fitness level (highest total throughput in our case) can lead to situation when some users' equipment have very high throughput, while other UEs can get very low throughput or none at all. It can be said that the system has low fairness. Term "fairness" in this case means providing the same level of service to all users of the network. For this reason, we propose an algorithm which provides a minimum throughput level to every UE. This is achieved by using a suggested sub-algorithm – bandwidth allocation.

In the next section, we describe the proposal. We start with description of the core part which exploits the GA to maximize the selected objective function and then continue with description of designed objective functions to maximize the throughput while guaranteeing at least minimal throughput of each user.

6.1. Description of the proposal

The core of the proposal is main algorithm based on genetic algorithm itself. It generates population, offspring, mutants and performs sorting and selection of the fittest individuals. It starts with initialization of genetic algorithm parameters, as shown in Figure 8. Generally, the scheme of the Cost function may be converged to the following sections:

- Setting basic parameters – it includes basic communication and genetic algorithm parameters.
- Generation of offspring, mutation, crossovers and selection – standard procedures of GA, which was described in previous.
- Finalization of main function – it includes merging of generated populations and performing selection of the fittest individuals.

All these sections are deexcited in more detail in next sub-sections.

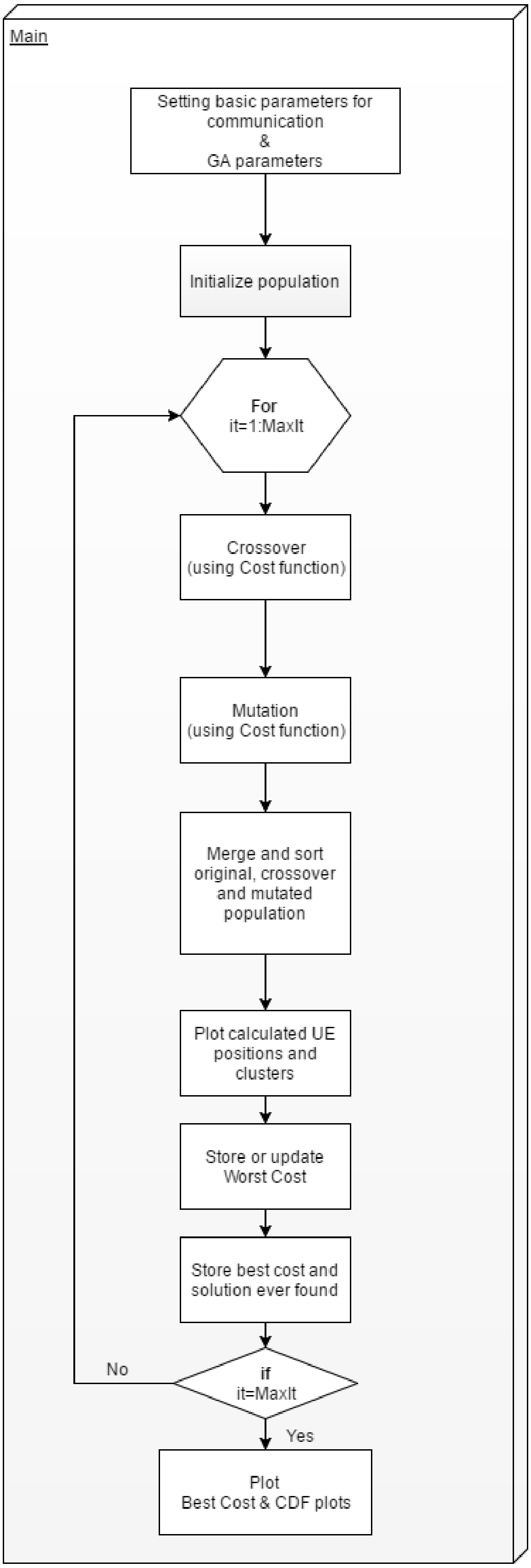


Figure 8. Main function block scheme.

6.1.1. Cost function

Second part of the algorithm, called Cost function is mainly responsible for non-genetic algorithm computations. The Cost function calculates fitness of the population for a given objective function. In our case objective function is to perform joint association and positioning. It is achieved by calculating throughput of each UE and total throughput in particular and performing clustering. Additionally, bandwidth allocation is made, if necessary. As a result, at the end of the run of this algorithm, an individual of a particular population group obtains its fitness parameter (total throughput value) and some additional data for further computations. General scheme of the Cost function is depicted at Figure 9.

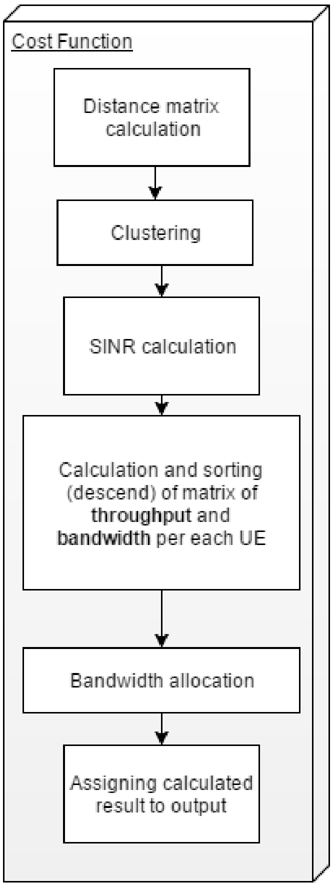


Figure 9. Cost function block scheme.

Considered blocks are responsible for calculation of distance matrix, SINR ration based on those distances and performing clustering – associating UEs with UAV. Firstly, the 3D distances between each UE and each UAV are calculated. Secondly, path loss for each UE should be calculated which is based on signal attenuation. As a result, we obtain received power of the signal for each UE from all UAVs.

Using calculated received powers of signals and knowing bandwidths of UAVs it is possible to calculate SINR. Standard formula is used:

$$SINR\ [dB] = \frac{P}{I+N},$$

where P denotes power of received signal, I denotes power of interference signals and N denotes thermal noise.

Calculating SINR of each UE and each UAV is necessary for clustering procedure. Clustering is performed by choosing the UAV to which the UE has the highest SINR value.

Next step is to allocate bandwidth per each UE in each cluster. It is performed by an equal distribution of total UAV bandwidth among all UEs that refer to that UAV cluster. After, throughput of channel (or capacity) between UEs and UAVs to which they are assigned is computed. In suggested model Shannon-Hartley capacity theorem is used due to 5G not being standardized to show what can be achieved:

$$C = B \cdot \log_2(1 + SINR)$$

Where C is the capacity of channel, B is the bandwidth allocated to the UE.

6.1.2. Bandwidth allocation

In order to achieve fairness of the system we exploit Water filling like approach proposed as Bandwidth allocation algorithm. Main idea of this sub-algorithm, described in is to balance the throughput of the UEs by reassigning bandwidth. This is due to direct relation between the allocated bandwidth and the throughput as shown in Shannon equation. We assume a set of eNBs (UAVs) $i \epsilon I$, set of UEs served by the i-th eNB $u \epsilon U_i$, bandwidth of the i-th eNB (or UAV) BW_i and the bandwidth assigned to the u-th UE b_u. The proposed algorithm works as follows: We go through all users served by a i-th base station (Steps 1 and 2). For each UE we calculate logarithm of its SINR from its serving eNB (Step 3). Then we normalize this SINR value (Step 5) and based on normalized SINR we divide bandwidth (Step 6).

Algorithm 1.

1. **For** each i in I
2. **For** each u in U_i
3. $\gamma_u = \log_2(1 + SINR_u)$
4. **end**
5. $\bar{\gamma}_u = \dfrac{\gamma_u}{\max(\gamma_u)}$
6. $b_u = \dfrac{BW}{\bar{\gamma}_u}$
7. **end**

7. System model and simulation parameters

Though, 5G network still doesn't have any exact specification, and most importantly radio access and frame structure defined. Therefore, for the purpose of performance evaluation of the proposed algorithm we rely on general communication channel - Adaptive White Gaussian Noise (AWGN) channel.

For the performance evaluation of the proposed algorithm MATLAB is used. In the simulation scenario we consider a simulation area of 800x800 m and uniformly distributed 500 static users with their UE. The UAVs are flying at altitude of 5 m. In Table 1 initial parameters of the simulation are depicted [17].

Table 1. Initial parameters of simulation.

Parameters	**Value**
Simulation area	800x800 m
Number of UE	500
Carrier frequency	2 GHz
Transmission power of eNB	43 dBm
Transmission power of FlyBS	23 dBm
Bandwidth of eNB	10MHz
Bandwidth of FlyBS	10MHz

It is also necessary to mention the parameters of genetic algorithm used in simulation Table 2). They are selected based on work in [18].

Table 2. Initial parameters of GA.

Parameters	**Value**
Number of iterations	100
Population size	500
Crossover percentage	80%
Mutation percentage	30%
Mutation rate	0,002

8. Scenarios

In this thesis, multiple simulation scenarios are considered. In first scenario, one UAV is considered. In second case, multiple UAVs are used in the same simulation with the same parameters.

8.1. Single UAV scenario

In this scenario influence of altitude of UAV on throughput is examined. Single UAV is deployed and its altitude is changed from 5m up to 30m as shown in Figure 10.

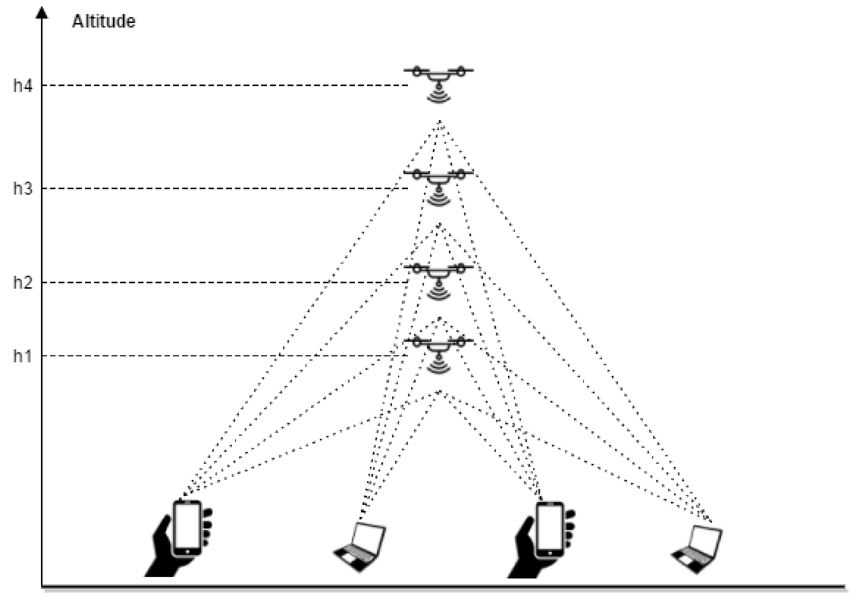


Figure 10. Altitude of the UAV.

Additionally, during this scenario the influence of altitude change on minimum threshold value is studied. All other parameters remain constant. This knowledge may be useful for the situation when at a calculated position of UAV may be some obstacle like tree or building for example. In such case, it is necessary to know whether it is better to change position or an altitude of a drone.

Example of positioning of UAV during one of the runs of algorithm is shown at the Figure 11.

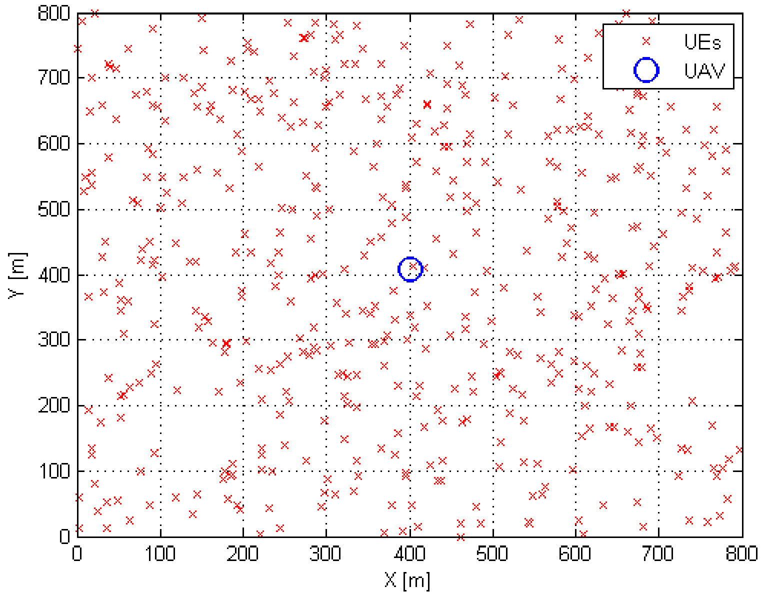


Figure 11. Single UAV scenario.

8.2. Multiple eNBs scenario

To show influence of number of UAVs on total throughput and minimum achievable throughput we increased number of deployed UAVs from 2 to 10. For comparison, we uniformly deploy eNBs to see the benefit of the UAVs which can be cooperatively positioned. Example of positioning of UAVs during one of the runs of algorithm is shown at the Figure 12

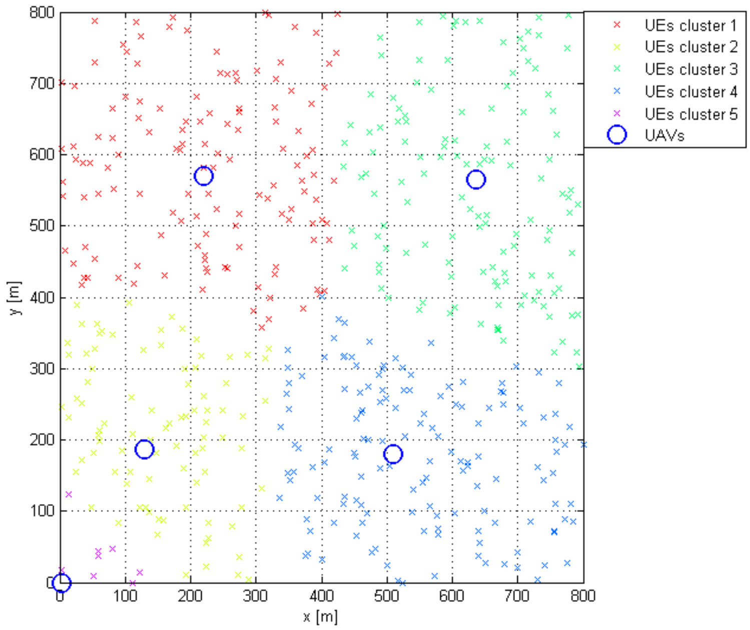


Figure 12. Example of positioning and association of 6 UAVs.

9. Simulation results

In this chapter, we do the performance evaluation and discuss the obtained results. Before providing performance evaluation, compared algorithm K-means is briefly described.

9.1. Description of k-means algorithm

The k-means algorithm partitions given space into clusters while finding centroids for each cluster [5]. Thus, it aims to a similar problem which we want to solve by the proposed algorithm. The k-means algorithm tries to minimize a so-called objective function that looks as follows:

$$F = \sum_j^k \sum_i^n \left\| x_i^{(j)} - y_j \right\|^2,$$

where $\left\| x_i^{(j)} - y_j \right\|^2$ is a distance between selected UE $x_i^{(j)}$ and cluster center y_j which refers to particular UAV position [1].

For comparison with genetic algorithm k-means algorithm was stocked with the same bandwidth allocation sub-algorithm.

9.2. Results of Single UAV simulation scenario

In this part of the thesis influence of altitude change is examined. There were selected following altitudes for UAVs: from 5 to 30 meters.

The influence of altitude on total throughput is shown in Figure 13. From the figure, it is visible, that total throughput is inversely proportional to the altitude of UAV. The reason of decay is an increase of distance between particular UE and UAV. As a result, path loss is increased which leads to greater wave attenuation and decrease of throughput of particular UE and total throughput as well.

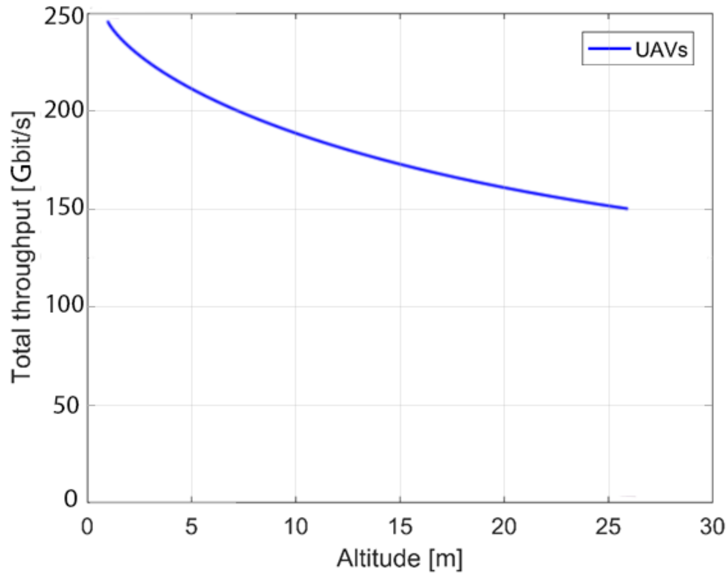


Figure 13. Relation of total throughput and altitude of a UAV.

Figure 14 shows cumulative distribution function (CDF) of SINR for altitudes 5, 15 and 30 meters. We can see that by increasing altitude, SINR is decreased by 2-3 dB. The reason for this that received power at UEs is decreasing, while interference is decreasing as well. Therefore, we see only a small decrease in the SINR.

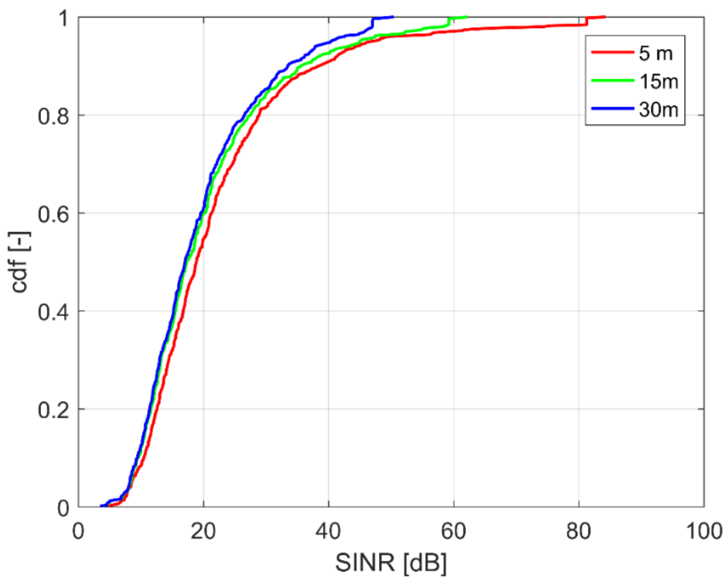


Figure 14. CDF of SINR for different altitudes.

In Figure 15 dependence of mean (as well as minimal and maximal) throughput of UE on altitude of UAV is shown. Throughput is exponentially decreasing with an increase of UAV altitude. We see that spread between maximal and minimal throughput is only $21.6 \cdot 10^6$ bits due to selection position of the UAV to provide fairness in the throughput and bandwidth allocation scheme.

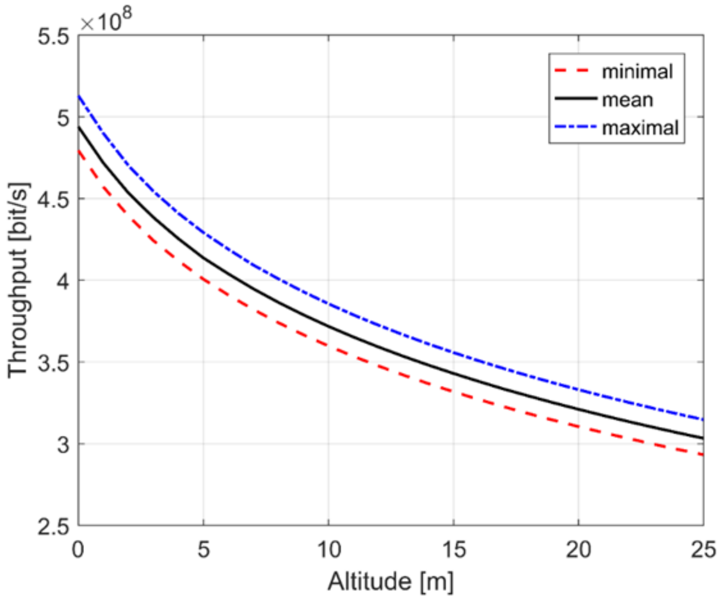


Figure 15. Dependence of throughput of an UE on UAV altitude change.

9.3. Results of multiple UAVs simulation scenario

In Figure 16 influence of number of cells (UAVs or fixed eNBs) on total throughput is shown. It is visible, that pure GA as well as k-means algorithm provides lower total throughput than in scenario with fixed eNBs. This is caused by a much higher transmission power of fixed eNBs (43 dBm vs 23 dBm). When switching on bandwidth allocation for both genetic and k-means algorithms, a rise of total throughput is observed, thogh GA constantly shows better perfomance then k-means algorithm. Gain of the GA with bandwidth allcoation is up to 15 % compared to k-means with bandwidth allocation and up to 1700 % compared to dense seployment of the eNBs.

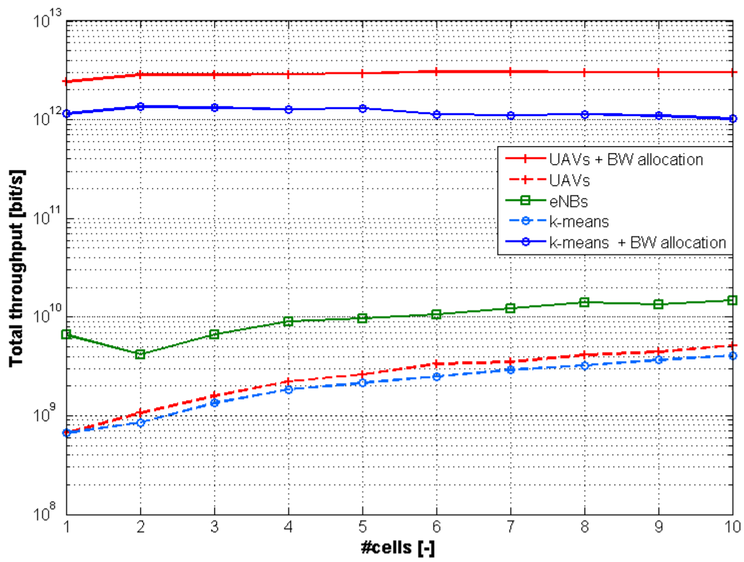


Figure 16. Dependence of total throughput on number of cells deployed.

In Figure 17 influence of number of cells on minimum throughput is depicted. Significant rise of minimum throughput with usage of bandwidth allocation is observed, though, k-means algorithm in most cases shows higher values. The k-means algorithm with bandwidth allocation provides minimal throughput higher by 38 % compared to the GA + BW allocation. This is due to primary focus of the proposal to improve total throughput.

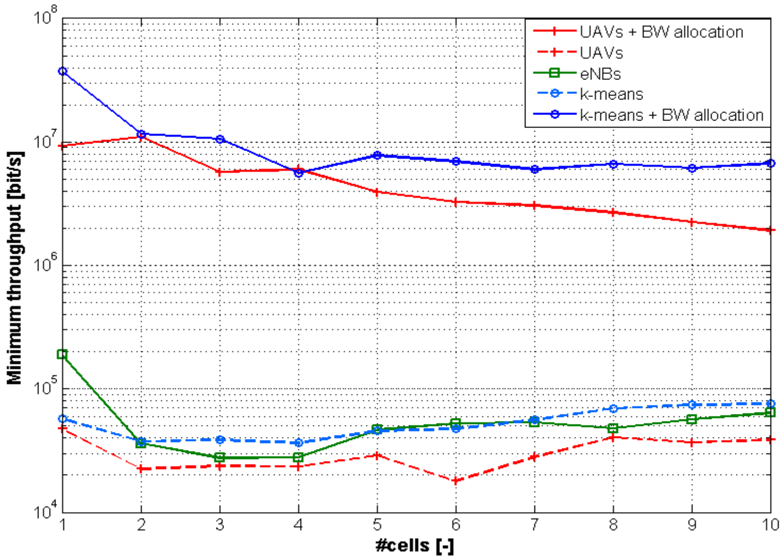


Figure 17. Dependence of minimum throughput on number cells

In Figure 18 we show influence of number of cells on average throughput. We see that the GA and the K-means algorithm provide similar mean throughput while BW allocation significantly increased the mean throughput. The gain of the GA with bandwidth allocation is up to 20% compared to the k-means with BW allocation.

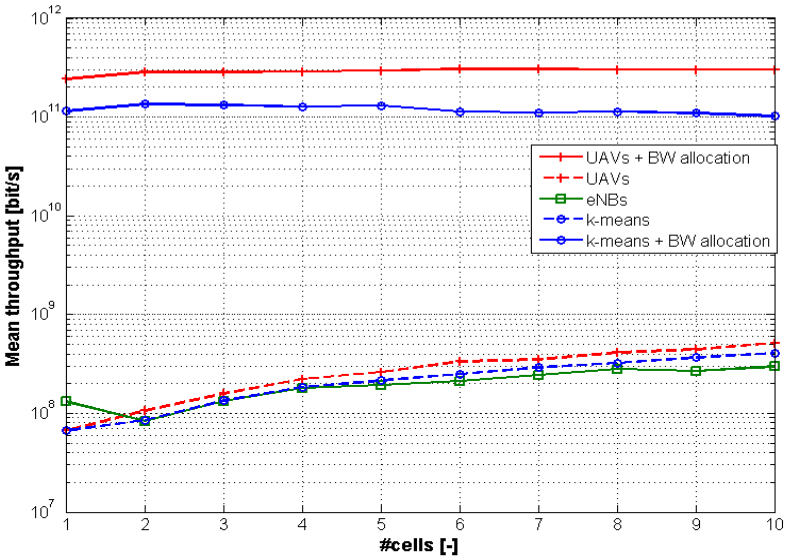
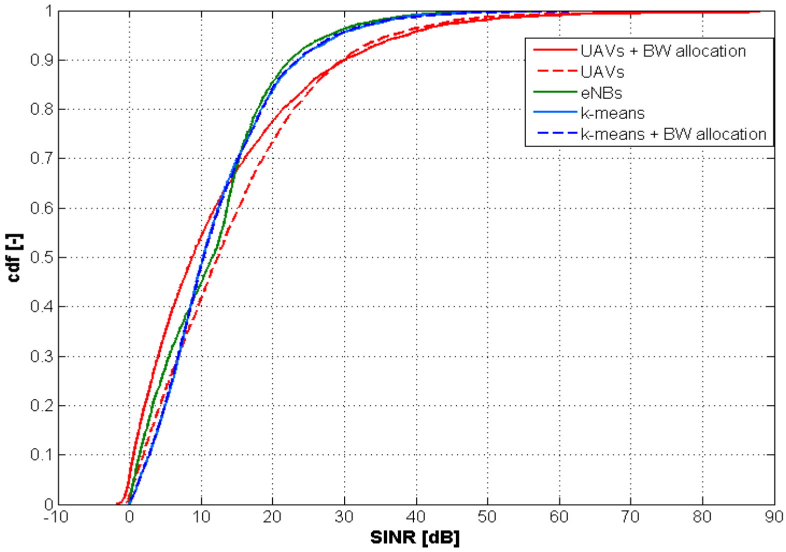
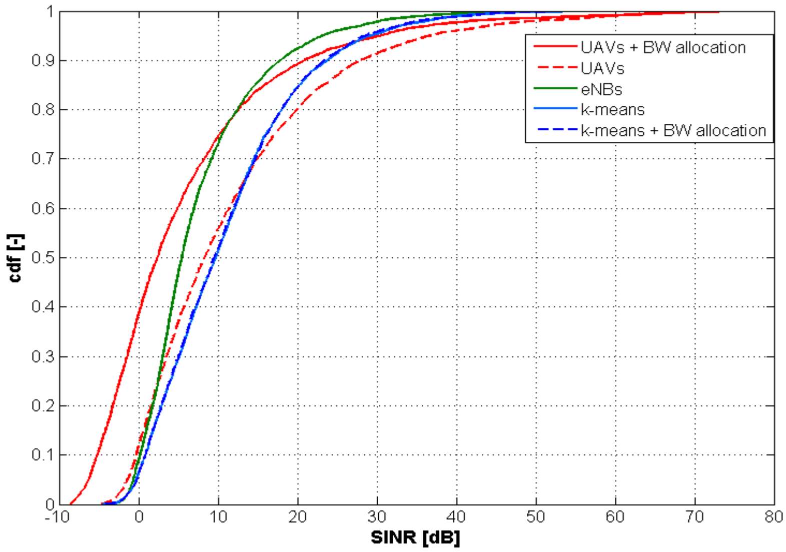


Figure 18. Dependence of mean throughput on number cells.

In Figure 19. CDF of SINR for all considered methods for different number of cells is shown. From this graphs it possible to observe that bandwidth allocation does not stress the need of a high SINR, compared to the GA. This is due to providing higher fairness between the users. By incrasing number of cells from 2 in Figure a. to Figure 19b. we see that SINR is decreases, which is caused by increasing interference due to incrased number of cells.



a)



b)

Figure 19. CDF of SINR for a) 2 cells, b) 10 cells.

Conclusion and future work

The aim of the thesis was to show how unmanned aerial vehicles can be used in mobile networks and to design algorithm for joint positioning of UAVs and association of UEs. Apart from the proposed algorithm bandwidth allocation scheme to provide fairness of throughput between users is proposed as well. The joint UAVs' positioning and UEs' association algorithm is based on genetic algorithm, while bandwidth allocation follows modified water-filling scheme. In this thesis, static users are considered to show the impact of the proposed solution compared to the existing algorithms.

In the performance evaluation, we show the impact of the UAV's altitude on throughput of users. It is shown that increasing of the altitude leads to decrease in the throughput. This decrease is following exponential decay, meaning that decrease in throughput versus increased in altitude is much lower. Therefore, positioning of the UAVs in three dimensions is possible with a small impact on the throughput.

Comparison of the deployment of multiple UAVs exploiting our proposed solution with k-means algorithm and ultra-dense deployment of eNBs is done. From the comparison, we see that relaying purely on the proposed algorithm without bandwidth reallocation leads to similar results compared to the k-means algorithm and worse results than the ultra-dense deployment of the eNBs. However, with bandwidth allocation our proposed algorithm in a case of total network throughput outperforms k-means and ultra-dense deployment of eNBs by 15% and 1700% respectively. Similar results are seen from the results of the mean throughput of users, where we see gain of 20% and 1720%, compared to k-means and ultra-dense deployment of eNBs respectively. In comparison of minimal throughput both k-means and the proposed solution outperform ultra-dense deployment of the eNBs. The proposed solution provides similar results as the k-means algorithms. From the results, we can conclude that the proposed solution outperforms the compared algorithms and therefore it is beneficial to deploy UAVs instead of dense deployment of the eNBs if temporal connectivity of large number of users is required.

In future work the algorithm can be improved to consider mobility of the users and by self-decision on how many UAVs are needed to cover certain area and provide a certain minimum threshold level.

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