Increasing the Cellular Network Capacity Using Self-Organized Aerial Base Stations

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ABSTRACT

Nowadays, the cellular network planning becomes a complex task due to unpredictable changes in mobile user behavior and high capacity requirements. Therefore, it is needed to deploy a high number of base stations in order to provide a requested quality of service. The advancement in technologies gives us an opportunity to use aerial base stations, which can change their positions in order to provide capacity only in space and time where and when it is needed.

In this work, we present a novel self-organized approach based on gradient search and potential fields for aerial base station deployment in order to increase the cellular network capacity. In contrast to the current aerial base station deployment approaches, our solution satisfies all requirements of modern urban scenario – it uses only local information, adapts to different environments, provides high degree of autonomy and scalability and operates in real time.

We provide a simulation-based evaluation of the proposed approach and a comparison to traditional base station placement in terms of the average aggregated system capacity. Results indicate that capacity can be improved by up to 52% in case of dense user clusters. Therefore network deployment costs can be minimized and spectrum efficiency maximized.

Keywords

Cellular system capacity; MAV; LTE; aerial base station; base station placement; self-organization

1. INTRODUCTION

User traffic demands are continuously growing along with quality of service requirements. More people are using data-demanding applications on their hand held devices, creating high expectations for cellular communication infrastructure. Traditionally, a set of ground base stations (BSs) is deployed to provide a service in a given area. The desired outcome of this process is twofold. First, the whole target area is needed to be covered, while it is not known in advance where mobile stations (MSs) will be located. Secondly, the capacity requirements of mobile users need to be satisfied. On the other hand, each BS can serve a limited number of mobile stations (MSs) dictated by the available system capacity. Therefore, in areas with a high density of mobiles the system capacity needs to be increased. In spatial domain the spectrum resource can be reused by decreasing the transmission range of each BS and increasing the overall number of BSs [1]. In this way, more users and traffic can be served.

According to studies in [2], the deployed infrastructure is not used the majority of the time, creating a waste of resources and requiring special algorithms in order to switch off unnecessary BSs to reduce energy consumption of the network. This way the energy consumption can be reduced up to 63%, which means that more than half of BSs are not used all the time.

Therefore, the traditional radio planning approach is not adaptive and scalable enough, introducing unnecessary costs for network support and deployment. Moreover, there are often overloaded and underloaded regions in the network. Thus, the spectrum resource is not used optimally in time and space.

New advances in technologies brought us cheap, small and powerful unmanned aerial platforms, which provide base station functionality. Current literature provide us with examples such as the micro-aerial vehicle with software-defined radio running a GSM BS [3] or the air balloon equipped with the LTE BS [4]. These solutions show a great potential for unmanned aerial platforms as an aerial base stations (ABSs).

The ABS can solve issues specific to the traditional approach by using the key functionality of unmanned aerial platforms - the capability of changing their positions. Using this capability the ABSs can be deployed in areas, where MSs are present and tune their position in order to provide the best communication conditions. Subsequently, the optimal aerial base station placement becomes the challenge.

In Section 2 a comprehensive overview of the state-of-the-art approaches is presented. In Section 3, we present a detailed description of the proposed novel self-organized placement approach for ABS. Section 4 provides the simulation evaluation and analysis of our results. In Section 5, the conclusions are drawn.

2. RELATED WORK

Historically, unmanned aerial vehicles were used in the military and for public safety for relaying purposes between

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two or more disconnected regions [5]. These solutions are not suitable for our scenario, since our target is not to maintain a connection between two entities, but to identify a group of MSs and to provide for them improved services.

Many researchers were attracted by the new possibilities of Aerial Base Stations (ABSs) inspired by commercial availability of unmanned aerial vehicles. For example, in [6] it was shown that the use of aerial relays can significantly reduce the downlink system loss in LTE/4G networks.

In [7] the relationship between altitude of ABS and coverage area was investigated. If an ABS is approaching the ground, the coverage area is reduced but the Quality of Service (QoS) is maximized. On the other hand, when an ABS is flying higher – the coverage area increases, while the QoS decreases. This provides us an interesting insight – in order to minimize interference and maximize QoS, not only the transmission power can be tuned, but the altitude can be changed creating a similar effect.

In [8, 9] authors are discussing the placement problem for multiple ABSs for a single snapshot. Trying different placement combinations in an iterative manner, they provide an answer to the question of how many ABSs are needed to be placed in order to maximize the number of served MSs. They assume that a global knowledge is shared among ABSs about locations and the number of served users, which requires a lot of signaling overhead and is not realistic in many scenarios. Mobility of users was not considered as well. Therefore, the application of the proposed approach is limited.

In [10] it was proposed to use a potential field concept in order to determine positions of ABSs. The algorithm maintains a certain number of best connections to neighboring ABSs using Received Signal Strength (RSS) measurements. Each ABS tries to find a gravity center of a potential field, which should correspond to a center of the MS crowd. However, the goal was to provide communication for only one crowd of users and create a mesh network between ABSs. In our opinion, several user crowds are usually present in urban scenario and moreover, the ABSs should not be close to each other in order to minimize interference and reuse the same spectrum resource.

3. SELF-ORGANIZED AERIAL BASE STATION PLACEMENT

In order to overcome previously mentioned limitations of the state-of-the-art approaches, an algorithm controlling the ABS should act in a self-organized manner and consider the current state of the radio environment in the decision-making process. Moreover, the ABSs should be able to successfully and robustly perform in scenarios, where minimum information is present.

There are two main challenges in the placement of aerial base stations. These are the localization of the target MSs and the placement of several ABSs in order to serve multiple MSs. The main issues are the ability to resolve conflicts between BSs, tracking several mobile MSs and dealing with a complex environment, e.g. on urban scenario. On the other hand, ABS should operate online, which does not allow to use exhaustive search algorithms.

Our proposed algorithm consists of three main phases:

- RSS signal filtering in order to deal with the signal noise;
- Gradient estimation based on RSS in order to determine the location of MS;
- Position estimation using potential field concept in order to track several target MSs and deal with the presence of other BSs.

Our approach proposes the following advantages over the existing work:

- RSS measurements are used, which provides the necessary insight into a real radio situation and the quality of the connection. Additionally, we do not require a complex hardware, as well as a global knowledge about BSs and MSs locations;
- ABSs and MSs are considered to be mobile and the proposed system should be able to track changes caused by mobility, which is not the case for related work;
- the ABSs decision process is based on a gradient search combined with potential fields. Each ABS acts in a distributed, self-organized manner without any centralized information. Moreover, ABSs avoid interference between themselves and other radio sources as well.

3.1 RSS Signal Filtering

In a real radio scenario there is a well-known indicator, which is available all the time – the RSS indicator. It incorporates the indirect information of real radio situation, including propagation model parameters and provides some rough information about the location of the signal source. Moreover, the link capacity can be estimated based on the RSS. The stronger the signal is, the more data can be encoded and transmitted over the medium [11]. The big advantage of the RSS indicator is that no extra hardware is needed since this measure is present in most radio technologies. In our previous work, RSS was proven to be an informative and robust indicator [3].

The problem of RSS indicator is that it includes noise and therefore highly fluctuates over time. In order to achieve precise measurements, it needs to be carefully filtered.

An example of the RSS, generated for suburban non-line-of-sight scenario, is shown in Fig. 1. It is filtered using mean and Kalman filters. According to these results, mean filters does not filter out unwanted fluctuations, e.g. fast fading. Moreover, a longer filter length introduces a delay, which can be crucial for the proposed algorithm.

The Kalman filter, which predicts the next value based on the physical model of the process, is considered as a superior alternative [12]. In case of an unmanned aerial vehicle, the dynamics of the process depend on the physical movement. This gives us an opportunity to use this knowledge in order to filter the signal.

It can be seen in Fig. 1 that the Kalman filter with the standard deviation of 10.9 and the process variance of $1e{-2}$ provides the best results. It captures the process dynamics (in this case, distance is increasing and RSS is lowering), can be executed in real time (gives an estimation at each step) and is very stable. The problem is that it introduces a slight offset to the reference signal without noise, which is due to the estimation error. On the other side, this is not important for the gradient search algorithm since it captures only relative changes in RSS instead of absolute values. After the filtering of the signal, the gradient search algorithm can be applied.

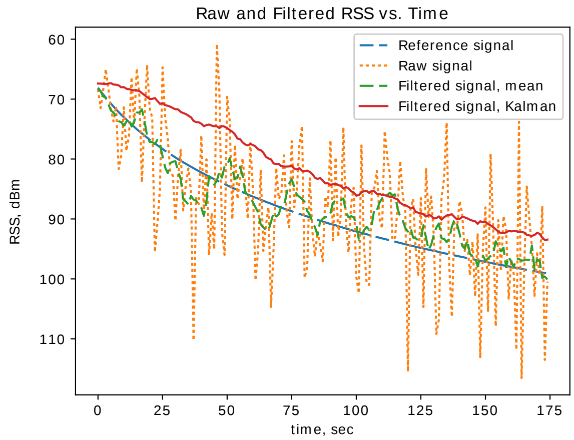


Figure 1: The comparison between different filtering approaches for RSS.

3.2 RSS Gradient Estimation

During the flight, the ABS is collecting n RSS measurements P_{rx} and saving the coordinates where the measurement was taken $pos = (x, y)$. The obtained pairs are called anchors.

$$(P_{rx_1}, pos_1), (P_{rx_2}, pos_2), ..., (P_{rx_n}, pos_n), \tag{1}$$

The number of anchors n corresponds to the size of a buffer. It is possible to estimate the RSS gradient using these anchors. First we need to calculate the partial derivatives for each axis. In our case it would be:

$$\nabla f = \frac{\partial F}{\partial x} e_1, \frac{\partial F}{\partial y} e_2, \frac{\partial F}{\partial P_{rx}} e_3, \tag{2}$$

where F is the vector of obtained anchors, e_1, e_2 and e_3 are standard unit vectors.

In order to achieve better estimation accuracy using a small number of anchors and since radio wave attenuation is a continuous process, interpolation of a gradient can be used. In this work, cubic interpolation is used. More details can be found in [13]. Since the goal is to generate a valid waypoint for the ABS, the point outside interpolated region should be chosen. For this task, extrapolation (prediction) is done using nearest method. After that, the point with the highest RSS can be chosen as an estimation of the signal source location.

The trajectory generated by the algorithm is shown in Fig. 2(a). The ABS can successfully converge to the signal source (one MS) in 2D space. The color code in the figure shows the travel time at each trajectory point. On the other hand, it can be seen that the algorithm behavior is not optimal and leads to a high convergence time. The point with coordinates (1100 m, 1100 m) becomes a first local minima for the gradient search algorithm. The ABS drifts to this point till it will collect enough non-colinear measurements to determine the direction to the signal source again.

Finally the trajectory turns into a spiral, unnecessary wasting time at local minimas. In order to avoid such behavior, more non-collinear anchors need to be collected. One of the solutions is to introduce an artificial noise to the trajectory. In our case, the artificial noise is introduced only when the ABS takes a straight curve for a specific amount of time. This way it can collect more anchors and estimate more accurate gradient. The resulting trajectory for the modified stochastic gradient search is shown in Fig. 2(b). According to 50 simulations runs, this approach can reduce the convergence time by 10% up to 50% depending on the speed of the ABS. Moreover, the stability of the resulting approach is much higher in comparison to the legacy gradient search algorithm.

According to our scenario, it is not enough to estimate and reach one target MS, but to serve multiple MSs and manage the interaction between multiple ABSs. The potential fields concept is introduced in order to achieve this.

3.3 Aerial Base Station Position Estimation Using Potential Field Concept

In order to achieve successful operation of ABSs, we need to identify an appropriate cluster of MSs and find the best location in order to provide communication services for them. Secondly, each ABS should define its own working area and avoid disturbance to the other BSs, which can be present nearby.

We propose to use a potential field concept in order to make the system flexible and self-organized. The idea behind the potential field concept is that charges with the same sign are repulsive and charges with the different signs are attractive to each other.

This approach can be adapted for our scenario: MSs are attractive entities, other ABSs and BSs are repulsive for a given ABS. Thus the utility function for a position estimation can be written as follows:

$$F(x, y) = w_{MS} \sum_{i=1}^{m} F_{MSi} + w_{ABS} \sum_{j=1}^{n} F_{ABSj}, \tag{3}$$

where F_{MSi} is the attractive force of MS, F_{ABSj} is the repulsion to other ABS, w_{MS} is the weight of the MS attractiveness and w_{ABS} is the weight of the ABS repulsion.

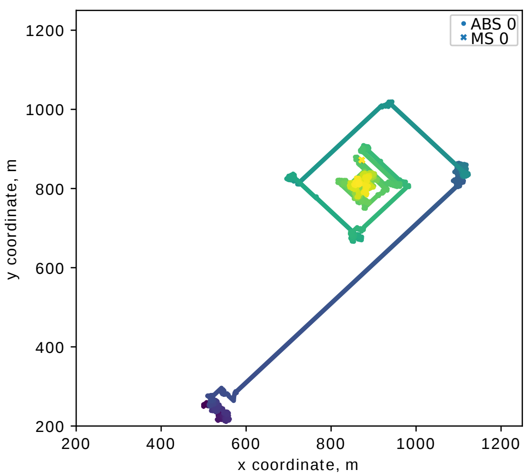
Tuning the weights of each term, the desired behavior can be obtained. In our scenario, it is important to balance the MSs attractiveness and ABSs repulsion in order to avoid situations, where all ABSs are attracted by a big cluster of MSs. Therefore, the direct relation between the number of ABSs and MSs can be set in the way that $w_{ABS} = m/n$.

Using the potential field concept the whole network is getting more resistant to failures of ABSs. In case if one ABS fails, then the repelling force to this ABS disappears and other ABSs will not consider it anymore. This means that the gap created by the failure of the ABS will be covered by other ABSs in the vicinity.

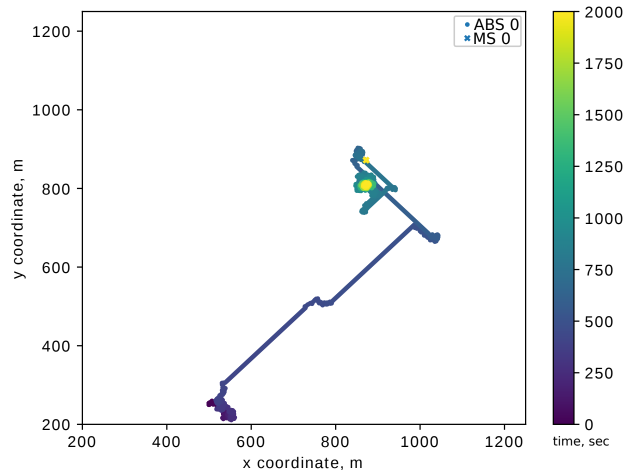
Based on Eq. 3, the resulting direction vector for the ABS can be obtained and fed to the control system of unmanned aerial vehicle as a waypoint.

4. SIMULATION EVALUTION

Coming back to the motivation of this work, it is important to compare the proposed approach to the traditional static BS placement approach, where BSs are located uniformly over the area in order to provide sufficient area coverage. In order to validate our approach, "Aerial Base Station Simulator" is used. We assume that ABSs are represented



(a) Legacy Gradient Search



(b) Stochastic Gradient Search

Figure 2: ABS trajectories during the search for the signal source in time.

by micro-aerial vehicles with the capability of hovering e.g. multi-copter.

4.1 Radio Propagation and Capacity Estimation Model

For interference estimation and communication purposes, a radio propagation model needs to be introduced. A log-distance path loss model with shadowing is used to model radio propagation effects in the urban environment [14]. In general, the path loss in decibel (dB) is expressed as:

$$PL = PL_{d_0} + 10\gamma \log_{10}(\frac{d}{d_0}) + X_g, \tag{4}$$

where PL_{d_0} is the path loss at the reference distance d_0, γ is the pathloss exponent, d is the length of the path and X_g is the normal random variable with zero mean and standard deviation σ, representing the shadowing effect. From Eq. 4, the received power can be calculated in dB as:

$$P_{rx} = P_{tx} - PL, \tag{5}$$

where P_{tx} is the transmitted power. Using derivations above, the system capacity can be calculated using Shannon's formula [11]:

$$C = W \log_2(1 + P/N), \tag{6}$$

where W is the system bandwidth, P is the received power of interest, N is the power of noise and interfering signals. P/N is the signal-to-interference-plus-noise ratio (SINR). N in its turn, is defined as:

$$N = K_B T_k W + \sum_{i=1}^{n} I_i, \tag{7}$$

where K_B is the Boltzmann constant, T_K is the temperature in Kelvin, I_i is the sum of the received power of interfering signals and n is the number of active interferers in a given moment of time.

4.2 Simulation Setup and Scenario

According to our previous practical experiments in [3], the most realistic scenario parameters were chosen and summarized in Table 4.2.

From one up to four BSs or ABSs were placed in the area of 2000 x 2000 m^2, as it is depicted in Fig. 3. All BSs are depicted by blue triangles and they were static during the whole simulations. All ABSs are depicted by yellow circles and their start positions were in the middle of the area (point (1000 m, 1000 m)).

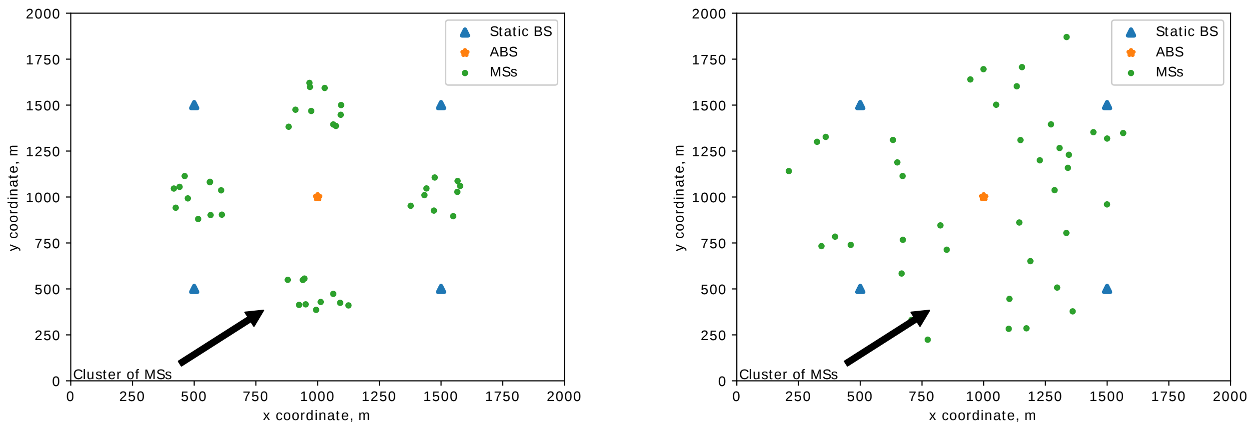
Two main simulation scenarios were investigated – either BSs or only ABSs were present in the area. Four MSs clusters with variable sparsity from 125 to 500 were located at the same area at the cell edges. The sparsity is defined as a radius of the cluster assuming that the cluster has a shape of a circle and the number of MSs is constant. The sparsity of the cluster represents different densities, where mobile users are crowds at minimal sparsity of 125 or are distributed almost uniformly over the area at maximum sparsity of 500. All MSs are inside the clusters and are located randomly and are static during simulations.

All BSs are assumed to be LTE-complaint and use the same frequency in order to maximize the spectrum reuse. Thus, all BSs are creating interference to each other. Each BS has six Resource Blocks (RB) of 180 kHz bandwidth, which can be used by any user and scheduled based on the highest SINR. In this simulation setup only the downlink situation is analyzed and the full buffer traffic model is assumed. In order to calculate average aggregated capacity for the network, the Shannon's capacity of all BSs is summed up and averaged over the simulation time.

For each of simulations, 16 runs were processed and then results were averaged to show the trend and eliminate sudden spikes due to random number generations.

4.3 Analysis of Simulation Results

The relationship between the average aggregated system capacity and the cluster sparsity is shown in Fig. 4 for the



(a) the cluster sparsity of 125 (high density)

(b) the cluster sparsity of 375 (low density)

Figure 3: Initial placement of BSs, ABSs and MSs for different cluster sparsities.

Parameter	Value/Name
Propagation model	Log-normal shadowing
Radio conditions	Suburban NLos area ($\gamma = 3.5$, $\sigma = 9.5$)
Simulation time step	0.1 sec
RSS arrival rate	0.5 sec
Frequency	1800 MHz
Transmit power	100 mW
Area size	2000 x 2000 m^2
ABS speed	8 m/s
Node distribution	Random uniform
Number of MSs	40

Table 1: Main simulation parameters.

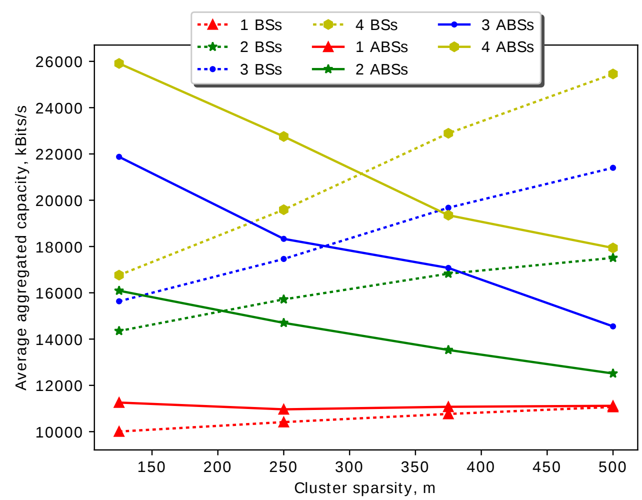


Figure 4: Average aggregated network capacity vs. cluster sparsity

proposed ABS and static BS placement. When cluster density is high, proposed approach demonstrates a high performance gain up to 52% (in case of four available BSs) in comparison to the static placement under challenging urban radio conditions. The reason is that each ABS adapts its own position in order to provide the best communication conditions for MSs, maximizes the spectrum efficiency and avoids interference to other BS.

Another interesting insight is that the proposed algorithm can minimize the number of the required ABSs. If the cluster sparsity is equal to 125, two ABSs can be used instead of four static BSs in order to achieve the same capacity. In case of cluster sparsity of 250, three ABSs can replace 4 static BSs. Therefore the infrastructure cost can be reduced.

When the density of clusters is getting lower, the static placement shows better results due to the optimal locations in case of uniform user distribution. On the other hand, the proposed approach shows non-optimal behavior due to the local minimas of the algorithm.

The results shows the feasibility of the proposed approach and significant gain in case of dense user clusters. The proposed approach is developed to be self-organized and thus, universal one. Therefore, it can be used to support the static BSs and to maximize capacity in all scenarios in case of high amount of users at cell edges.

5. CONCLUSION

This paper presented a novel self-organized approach for the deployment of aerial base stations in order to increase the cellular network capacity. ABSs can change their positions in order to provide capacity only in space and time where it is needed. In contrast to the state-of-the-art approaches, our solution satisfies all requirements of modern urban scenario – it uses only local information, adapts to different environments, provides high degree of autonomy and scalability.

Simulation results showed that the proposed approach provides significant gain in terms of the system capacity in comparison to the static BS placement. The average aggregated capacity can be improved up to 52% using the opportunity to change the positions of ABSs. To provide the same capacity we would need to use twice as many BSs than ABSs.

The coordination of ABSs can be achieved exploiting simple self-organization concepts. To this purpose, it is not necessary to provide ABS with a complex behaviors. Instead, we show a minimal complexity of the algorithm is sufficient to achieve the high performance gain in terms of system capacity.

This proofs that the proposed solution can be used in the future networks under challenging radio conditions.

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