Autonomous Self-deployment of Wireless Access Networks in an Airport Environment

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Abstract. In environments with highly dynamic user demand, for example in airports, high over-dimensioning of wireless access networks is required to be able to serve high user densities at any possible location in the covered area, resulting in a large number of base stations. This problem is addressed with the novel concept of a self-deploying network. Distributed algorithms are proposed, which autonomously identify the need of changes in position and configuration of wireless access nodes and adapt the network to its environment. It is shown that a self-deploying network can significantly reduce the number of required base stations compared to a conventional statically deployed network. In this paper, this is demonstrated in a specific test scenario at Athens International Airport, simulating a moving user hotspot after the arrival of an airplane.

1 Introduction

In an airport environment, the arrival and departure of airplanes results in a highly dynamic environment. User demand and positions are changing rapidly with the result that high over-dimensioning of wireless access networks is required to meet the need of high bandwidth services at any possible hot-spot location. In this paper, autonomous adaptation of base station positions is investigated as a possible means to reduce the total number of required base stations in such environments. Such self-deploying network [1] would be able to identify the need for changes in both base station positions and configuration, and implement these changes without human intervention. The potential reduction of required base stations is investigated in a specific scenario at Athens International Airport, simulating a moving user hotspot after the arrival of an airplane. Mobile base stations are considered which are deployed on a rail at the ceiling of the terminal building, and are able to move autonomously along this rail, as illustrated in Fig. 1. Instead of over-dimensioning the network for the highest expected user density at any possible location, mobility of base stations allows it to adapt autonomously to changes in user locations and demand with the result of a significantly reduced number of required base stations.

While base station mobility might seem futuristic for commercial wireless communication systems (due to the costs involved in providing base station mobility), this concept has near-term applications in the field of military and emergency communications, where fast network deployment is required in high-risk areas or in environments

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that are difficult to access. The airport scenario was chosen for its simplicity in order to minimise the computational complexity of the environment simulation and to demonstrate the proposed algorithms, which are not limited to such a one-dimensional self-deployment implementation.

Base station positioning has been studied extensively in the past, using simulated annealing [2,3], evolutionary algorithms [4], linear programming [5], and greedy algorithms [6,7]. Other work has explored the trade-offs between coverage, cell count and capacity [8]. It has been shown that the identification of the globally optimum base station locations in a network of multiple base stations is an NP-hard problem, far too complex to solve computationally [4-6]. Further difficulties are that most of the system parameters required to find an optimal solution are unknown, and the optimal positions change constantly due to the changes in user demand, user positions, and base station positions.

The objective is the development of algorithms that are able to find near-optimum solutions for self-deployment and self-configuration, based only on limited local system knowledge. To achieve a high robustness and scalability, radically distributed processing which results in self-organising behaviour is investigated. An additional objective is to avoid or minimise direct communication between base stations in order to reduce the signalling overhead and allow technology independent operation. In this way, the network may consist of base stations with different access technologies such as UMTS or 802.11.

This paper is organised as follows. In Section 2, the use of stigmergy [9] for indirect communication between base stations is investigated in order to achieve a globally self-organising behaviour of base station locations in a network. In Section 3 the difficulties involved in finding the optimal locations of base stations in a network are discussed. Globally and locally optimal solutions are presented and modified, to allow self-deployment with limited local system knowledge. Simulation results in an airport scenario are presented in Section 4 and finally, conclusions are drawn in Section 5.

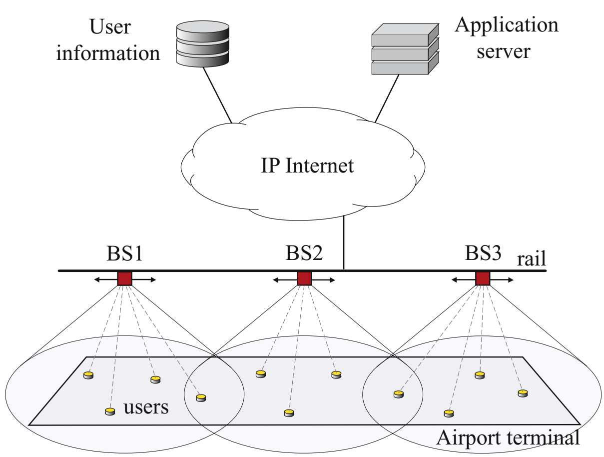


Fig. 1. Autonomous, self-deploying wireless access network. Mobile base stations are mounted on a rail in an airport environment.

2 Self-deployment and Stigmergy

Avoiding direct communication between base stations makes the optimisation problem very challenging since some means of communication is necessary to optimise the network globally. This problem may be addressed by using indirect communication, where each base station modifies its surrounding environment, and these changes then influence the behaviour of neighbouring base stations. In the field of biology, such interaction is known as stigmergy and is widely used by social insects to coordinate their activities by means of self-organisation (e.g. ants use decaying pheromone trails to find shortest paths).

In wireless communication systems, the environment in the network relates to the connections to the mobiles. When mobiles connect to the base station with the strongest received control pilot power, these connections provide information on the coverage of neighbouring cells. One possible driver for a change in the network environment is the modification of base station positions. Other possibilities are, for example, changing user demand or the adaptation of the pilot powers to achieve load balancing (either equal transmit power, or equal capacity) in each cell. The modification of the network environment through re-positioning or load balancing provides an indirect way of communication between the base stations.

One advantage of the proposed indirect communication is that it can be considered as a universal language which allows interoperability of heterogeneous systems (i.e. systems with different access technologies) since base stations do not need to be able to exchange data directly with other base stations in the network.

Examples:
An example of the self-organisation process, resulting from indirect communication between base stations and local optimisation of each base station location is illustrated in Fig. 2. Base stations are shown as solid squares and mobiles are shown as circles with a line to the connected base station. The optimal base station positions are shown as squares.

Start condition:

All mobiles are connected to the base station dependent on the connection rule (strongest received control pilot power). This defines the current network environment.

Continuous self-deployment process:

- In each step, the optimal positions for all base stations are calculated, based on the current network environment (i.e. connections) seen by each base station.
- In each following step, all base stations move to the optimum positions predicted in the previous step.
- The new base station positions trigger a change in the connection to the mobiles.

A further example showing the self-deployment process triggered by load balancing via modification of the pilot powers is shown in Fig. 3. The contour plots illustrate the received control pilot power. When BS2 reduces its pilot power for load balancing (Step 1), BS1 takes over several connections (Step 2). As a result, both base stations optimise their positions for their changed connections (Step 3).

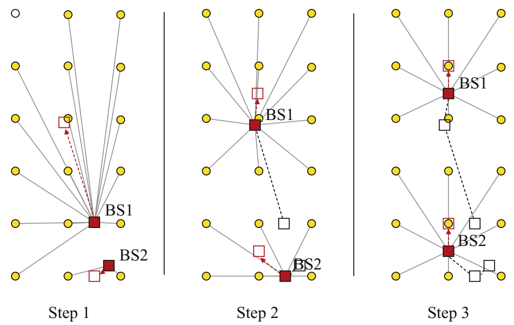


Fig. 2. Self-deployment using stigmergy

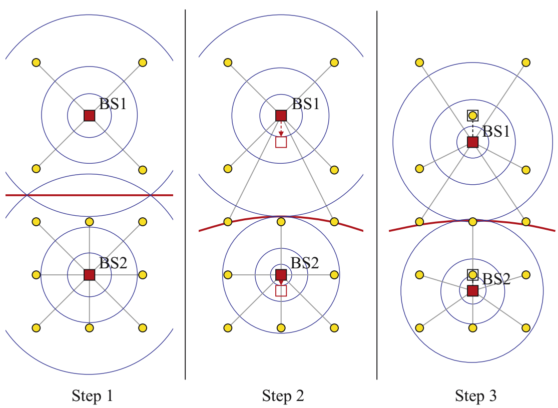


Fig. 3. Load balancing through re-positioning of base stations

3 Base Station Positioning Algorithms

The optimal position of a base station can depend on a variety of factors. While optimisation of the resource efficiency is an obvious criterion, other factors or constraints such as suitable locations, costs, or legislation also play an important role. This investigation, is focussed on the optimal use of resources (i.e. transmit power and available frequency spectrum), within constraints such as maximum transmit power levels of single base stations or possible locations. From this standpoint, rules for optimal positioning of individual base stations, and base stations in a network, can be stated as follows:

> *Rule1: Local optimisation of individual base stations*
> The optimal position for an individual base station allows it to sustain all requested connections with the minimum possible transmit power.
>
> *Rule 2: Global optimisation of base stations in a network*
> The optimal positions of all base stations in a network allow the network to sustain all requested connections with the minimum possible transmit power.

Note that both rules are subject to constraints, and the locally optimum position of a single base station according to Rule 1 is not necessarily equivalent to the position of the same base station in a globally optimised network based on Rule 2.

To satisfy the minimum possible transmit power criterion for an arbitrary small bit-error rate, the receivers must operate at the Shannon capacity limit. In fact, recent advances in coding theory (turbo codes, LDPC codes) allow communications very close to the capacity limit even in the presence of fast fading. Therefore, the capacity limit itself may be targeted as the optimisation point for the wireless access network.

The following assumptions are made: In order to use simple capacity equations, the intra- an inter-cell interference is modelled as a white Gaussian random variable with zero mean. This can be justified by arguing that for a large number of interferers, the total interference becomes Gaussian. In addition, only the slow fading components of the channel are taken into account for the base station positioning.

3.1 Minimum Power Requirement for a Link with Given Capacity

The channel capacity C for a channel perturbed by additive white Gaussian noise is a function of the average received signal power $P_{\mathrm{Rx}} = \mathrm{E}\{s(t)s(t)^*\}$, the average noise power $N = \mathrm{E}\{n(t)n(t)^*\}$ and the bandwidth B, where $s(t)$ and $n(t)$ denote the signal and noise values at the time instant t. The well known capacity relationship (Shannon-Hartley theorem [10]) can be expressed as

$$C = B\log_2\left(1+\frac{P_{\mathrm{Rx}}}{N}\right). \tag{1}$$

In order to write (1) in terms of transmitted power P_{Tx}, the impact of the channel loss $L = L_{\mathrm{p}} \cdot L_{\mathrm{s}}$, characterised as a combination of attenuations resulting from path loss L_{p} and shadow fading L_{s} and must be taken into account. Note that this requires knowledge of the positions of the connected mobiles and knowledge of the environment (i.e. shadow fading properties). In addition, gains at the base station and the mobile, G_{BS} and G_{UE}, can be included. Then, the channel capacity can be rewritten as

$$C = B\log_2\left(1+\frac{P_{\mathrm{Tx}} \cdot G_{\mathrm{BS}} \cdot G_{\mathrm{UE}}}{N \cdot L}\right). \tag{2}$$

Finally, the minimum required transmit power for a radio link of capacity C for given values of bandwidth B, channel attenuation L and received noise N (including interference) operating a factor of α from the capacity limit, can be determined as

$$P_{\mathrm{Tx}} = \frac{\alpha \cdot N \cdot L}{G_{\mathrm{BS}} \cdot G_{\mathrm{UE}}}\left(2^{C/B}-1\right). \tag{3}$$

Here, the capacity C represents the requested data rate and the bandwidth B of the radio link is known.

3.2 Globally Optimum Positioning

For joint optimisation of the whole network, the optimal positions of all base stations minimise the total transmitted power for all requested links (Rule 2). The optimum set of coordinates for all M base stations and all K_m requested links to the mth base station can be written as

$$(\mathbf{x}_{\text{opt}}, \mathbf{y}_{\text{opt}}) = \arg\min_{(\mathbf{x},\mathbf{y})} \left\{ \sum_{m=1}^{M} \sum_{k=1}^{K_m} P_{\text{Tx},m}^{(k)}(x_m, y_m) \right\}, \tag{4}$$

where $(\mathbf{x}, \mathbf{y}) = (\{x_1 \ldots x_M\}, \{y_1 \ldots y_M\})$ is the set of possible base station position coordinates. The indices for the base station and the link are denoted by m and k, respectively. $P_{\text{Tx},m}^{(k)}(x_m, y_m)$ denotes the required transmit power from (3) for the kth link of the mth base station at the coordinates (x_m, y_m) within the possible region of deployment.

Alternatively to using specific connections for the calculation of the required transmit power $P_{\text{Tx},m}^{(k)}(x_m, y_m)$, the above problem may be solved for a given user and demand distribution. Then, for each potential user location the expected value E{ $P_{\text{Tx},m}^{(k)}(x_m, y_m)$ } may be used instead. Each base station can collect the required user statistics during operation. This approach results in the average optimum position and can be used to optimise the positions of non-mobile base stations that require human intervention to move.

The optimisation of (4) implies a search over a very large number of candidates, which grows exponential with the number of base stations. Therefore, an exhaustive search for jointly optimal positions for more than a few base stations in a limited area is impractical due to prohibitive computational complexity (i.e. NP-hard problem). In addition, centralised processing is necessary and complete system knowledge is required. However, in reality most of the required parameters (e.g. channels and interference at new positions) are unknown. Therefore, even if the computational complexity were manageable, it would still be impossible to compute the globally optimum positions due to incomplete system knowledge.

3.3 Locally Optimum Positioning

For each individual mth base station, the position can be optimised locally, by searching for a position, which minimises its transmitted power for all K_m requested links (Rule 1). Then, the locally optimum coordinates of each mth base station may be calculated as

$$(x_{\text{opt}}, y_{\text{opt}}) = \arg\min_{(x_m, y_m)} \left\{ \sum_{k=1}^{K_m} P_{\text{Tx},m}^{(k)}(x_m, y_m) \right\}. \tag{5}$$

Again, the optimisation problem may be solved for a given user and demand distribution instead of for specific connections by using the expected value of the transmit power, required at each potential user location.

In contrast to the global optimisation, the local optimisation can be solved in a decentralised manner, based only on local system knowledge. However, as before, not all of the required system knowledge is available. At each potentially new base station position, the channel conditions (i.e. L_s), and therefore also the interference at both, mobiles and base stations, are unknown.

3.4 Positioning with Limited System Knowledge

As shown in Section 3.2, the globally optimal positioning of networks is a challenging task due to limited knowledge of the constantly changing system parameters and the prohibitive computational complexity. The locally optimum solution of Section 3.3 is of manageable computational complexity, but suffers from the same problem of incomplete system knowledge. As a consequence, other solutions based on partial system knowledge are required that provide results close to the optimum solution.

Current values for shadow fading and interference levels seen by each node can be easily measured. However, when the base station positions change relative to the interference sources, both, the shadow fading values and also the interference, can change unpredictably. Therefore, the shadow fading values L_s, and the interference levels, which dominate N in (3), at any new potential base station position can be considered as unknown. Under this assumption, the local optimisation criterion of (5) may be modified to

$$(x_{\mathrm{opt}}, y_{\mathrm{opt}}) = \arg \min_{(x_m, y_m)} \left\{ \sum_{k=1}^{K_m} \varphi_m^{(k)}(x_m, y_m) \right\}, \tag{6}$$

with

$$\varphi_m^{(k)}(x_m, y_m) = \frac{\alpha \cdot L_{\mathrm{p}}}{G_{\mathrm{BS}} \cdot G_{\mathrm{UE}}} \left(2^{C/B} - 1\right). \tag{7}$$

The strategy is to take any knowledge available into account, and ignore (or replace with their expected value) all unknown contributions. Here, L is replaced with L_{p}, since $\mathrm{E}\{L\} = L_{\mathrm{p}}$ and N is ignored. Alternatively, N could be estimated by calculating inter-cell interference based on path-loss only, and assuming constant intra-cell interference.

Equation (6) represents a convex optimisation function that can be solved using either an exhaustive search, or less complex approaches such as steepest descent or conjugate gradient methods [11].

4 Simulation Results

In order to evaluate the impact of autonomous self-deployment on the required number of base stations, both conventional and self-deploying wireless access networks were simulated for a specific test scenario in the terminal building at Athens International Airport. The scenario is illustrated in Fig. 4, where base stations are shown as solid squares and mobiles are shown as circles with a line to the connected base station. The arrows indicate the movement of the user hotspot.

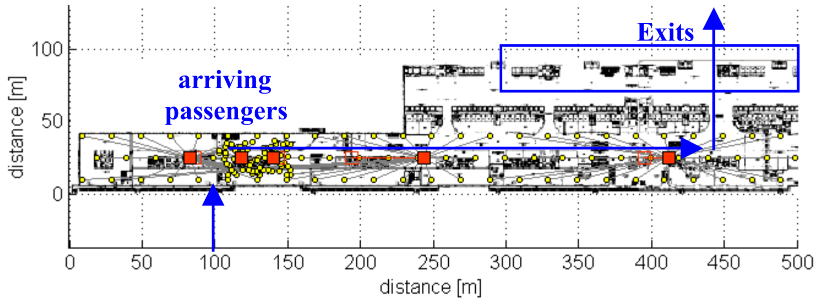


Fig. 4. Test scenario in the terminal building of Athens International Airport

Simulation steps:

(a) Start condition: uniform user and base station distribution along the terminal corridor.
(b) An airplane arrives and the passengers create a user hot-spot (shown in Fig. 4)
(c) The arriving passengers move along the corridor in direction of the airport exits (indicated by arrows).
(d) The arriving passengers leave the airport, and the user hotspot disappears.
(e) Finally, the user distribution becomes uniform again.

System level simulations were performed for the downlink of a generic wireless system to identify both the required number of base stations and the network performance, in terms of total required transmit power, for self-deploying and conventional networks. The evaluation was performed in an iterative manner until a convergence point for the link transmit powers was reached. In this way it is possible to take into account that the transmit power of each link depends on the powers of all other links in the system, and vice versa. It is assumed that each mobile connects to the base station with the highest received control pilot power. Load balancing via modification of the control pilot power is employed such that all base stations try to stay within both power and capacity limits. An additional pilot for channel estimation is assumed to require 10% of the transmit power used for data at each base station. For each simulation step, the evaluation was performed as follows, using the parameters shown in Table 1.

$P_{\mathrm{BS}}(0) = \mathrm{zeros}(M)$ % *initialise base station powers with zeros*
for $i = 1 \ldots I_{\max}$ % *for a maximum of I_{max} iterations*
  for $m = 1 \ldots M$ % *for all M base stations*

$$P_{\mathrm{BS},m}(i) = \sum_{k=1}^{K_m} P_{\mathrm{Tx},m}^{(k)}(i-1) + P_{\mathrm{pilot}} \quad \text{\% calculate BS powers} \tag{8}$$

$$\delta_m(i) = \left| P_{\mathrm{BS},m}(i) - P_{\mathrm{BS},m}(i-1) \right| / P_{\mathrm{BS},m}(i) \tag{9}$$

  end
  if $\max(\delta_m(i)) < 0.01$ % *convergence criterion*
    break; % *break iterations when BS powers are converged*
  end
end

$$P_{\text{Network,DL}} = \sum_{m=1}^{M} P_{\text{BS},m}(i) \qquad \text{\% network performance metric} \tag{10}$$

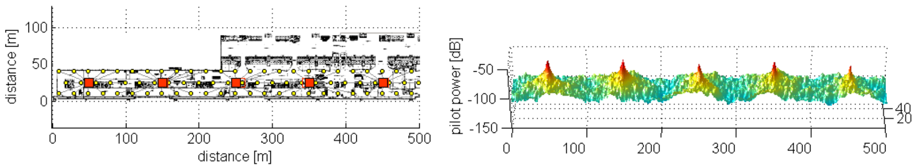
In each iteration i, the inter-cell interference required for the calculation of $P_{\text{Tx},m}^{(n)}(i-1)$ can be calculated based on the transmit power of each mth interfering base station as $P_{\text{I,inter}} = L\,P_{\text{BS},m}(i-1)$ from the previous iteration, where L is the channel loss between the interference source and the receiver of interest. When multiple links are served simultaneously from a single base station, the intra-cell interference for the nth link of the mth base station can be calculated as $P_{\text{I,intra}} = L[P_{\text{BS},m}(i-1) - P_{\text{Tx},m}^{(n)}(i-1)]$, based on values from the previous iteration.

Table 1. Simulation parameters

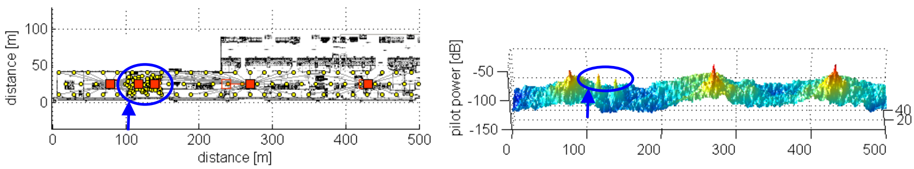
Parameter	*value*
Maximum BS transmit power	0.25 W
Maximum number of users per BS	32 users
Channel bandwidth B	3.84 MHz
Link capacity C	64 KBit/s
BS antenna gain – cable loss $G_{\text{BS,[dB]}}$	5 dB
UE antenna gain – cable loss $G_{\text{UE,[dB]}}$	0 dB
Operation point (from channel capacity) $\alpha_{\text{[dB]}}$	7 dB
UE noise figure $NF_{\text{[dB]}}$	10 dB
Shadow fading standard deviation	6 dB
Shadow fading spatial correlation	$r(x)=e^{-x/20}$
Path loss $L_{\text{p,[dB]}}$	37+30log(d) dB
Maximum BS speed	5 m/s

For the optimisation of the base station locations, the positioning algorithms based on limited local system knowledge of (6) and (7) are employed and solved by using a simple steepest descent algorithm. It is assumed that each base station has knowledge of the path loss, but the shadow fading variations are unknown. A spatially correlated shadow fading environment was generated as described in [12].

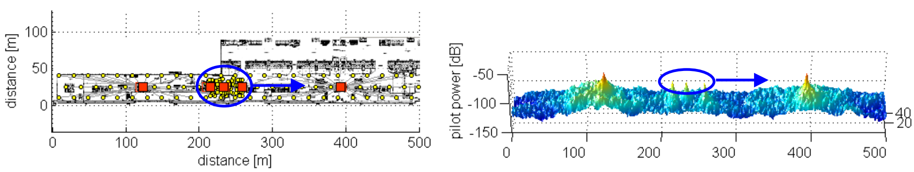
The simulations indicate that the self-deploying network requires at least five mobile base stations to serve all user requests of the simulated scenario. The user and base station locations, and the control pilot power during the autonomous self-deployment process are depicted in Fig. 5. As start condition, all base stations are uniformly distributed to provide service to a uniform user distribution of 75 mobiles (a). Then a plane arrives and the passengers create a user hotspot of additional 75 mobiles (b). The capability of autonomous repositioning allows the base stations to adapt to the changing user and demand distributions and move to the user hotspot to increase the capacity in this region. When the users move in direction of the airport exits, the base stations follow their movement and hand the users over to their neighbouring base stations (c). In this way, a small number of base stations have the ability to serve a large number of users in highly dynamic scenarios. Arriving at the exits the users leave the airport and the hotspot disappears (d). As a consequence, the base stations spread out again to serve the remaining users (e).



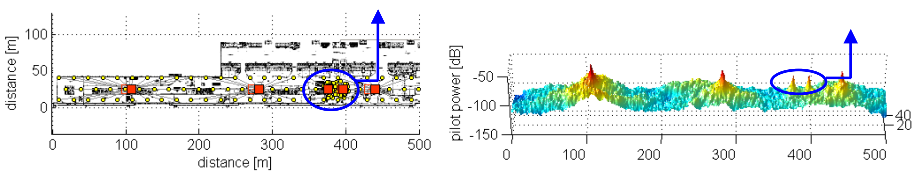
(a) Uniform user distribution along the gates



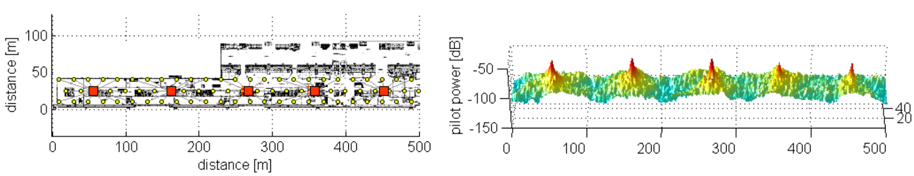
(b) A plane arrives and the passengers create a user hotspot. Base stations move to the user hot-spot to provide the required capacity.



(c) The users move along the corridor to the airport exits. Base stations follow their movement.



(d) Arriving at the exits, the users leave the terminal building (hotspot disappears).



(e) The base stations spread out uniformly to serve the remaining users

Fig. 5. Simulation steps of a self-deploying network in an airport environment. A minimum number of five mobile base stations is required for this scenario.

In the same scenario, a conventional wireless access network with fixed base station deployment requires at least nine base stations to achieve similar performance as the self-deploying network. This over-dimensioning is required to allow the network

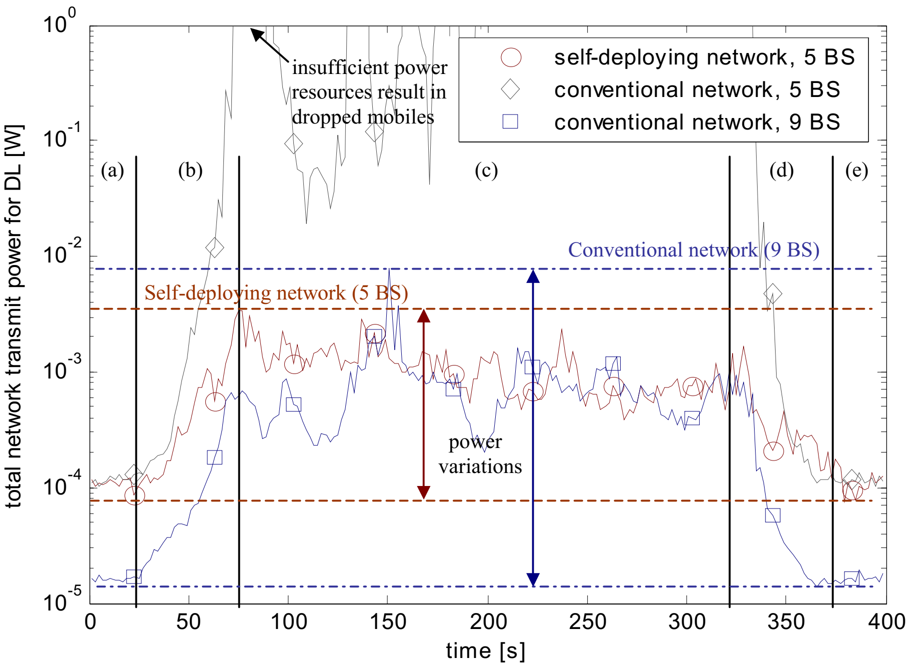
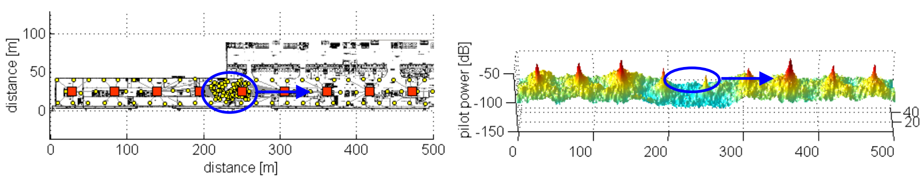


Fig. 6. Performance comparison of self-deploying and conventional networks



(c) The users move along the corridor to the airport exits.

Fig. 7. Simulation step of a conventional network with fixed base station deployment in an airport environment. A minimum number of nine base stations are required to achieve a similar performance as the self-deploying network with five base stations.

to cope with the moving user hotspot, without having the ability of base station repositioning. Therefore, it must be dimensioned for the highest expected user density at any possible location.

Figure 6 depicts a performance comparison of conventional and self-deploying networks. It is shown that a self-deploying network with only five base stations is able to outperform a conventional network with nine base stations. In addition, the self-deploying network shows much less variations in the required transmit power. A conventional network with five base stations exceeds the maximum base station power resources, and therefore is not able to provide all requested services in the test scenario.

The results confirm that self-deploying wireless access networks are able to significantly outperform conventional networks, since they are able to adapt effectively to changing user demand and user locations, and therefore do not require high over-dimensioning as conventional networks to cope with dynamic network environments.

5 Conclusions

In this paper, the concept of a self-deploying wireless access network was used to reduce the required number of base stations in highly dynamic environments. Distributed algorithms based on the channel capacity were proposed that are able to autonomously identify required changes in position and configuration of wireless access nodes, dependent on the demand and locations of users. It was shown that self-deploying networks using the proposed algorithms are able to significantly outperform conventional networks with fixed base station positions. For the investigated test scenario at Athens International Airport, this resulted in a reduction of the required number of base stations from nine, for the conventional network, to only five self-deploying base stations with improved network performance. This promising result demonstrates the potential advantages of autonomous, self-deploying wireless access networks. Future research will have to investigate both, technical robustness and economic viability of such self-aware and self-designing networks, critical for the widespread adoption in next-generation wireless access architectures.

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