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Dynamic Self-Optimization of the Antenna Tilt for Best Trade-off Between Coverage and Capacity in Mobile Networks

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Abstract One major factor influencing the coverage and capacity in mobile networks is related to the configuration of the antennas and especially the antenna tilt angle. By utilizing antenna tilt, signal reception within a cell can be improved and interference radiation towards other cells can be effectively reduced, which leads to a higher signal-to-interference-plus-noise ratio received by the users and increased sum data rate in the network. In this work, a method for capacity and coverage optimization using base station antenna electrical tilt in mobile networks is proposed. It has the potential to improve network performance while reducing operational costs and complexity, and to offer better quality of experience for the mobile users. Our solution is based on the application of reinforcement learning and the simulation results show that the algorithm improves significantly the overall data rate of the network, as compared to no antenna tilt optimization. The analysis in this paper focuses on the downlink of the cellular system. For the simulation experiments a multicellular and sectorized mobile network in an urban environment and randomly distributed user terminals are considered. The main contribution in this work is related to the development of a learning algorithm for automated antenna tilting.

Keywords Mobile networks · Self-optimization · User satisfaction · Antenna tilt · Coverage · Capacity · Machine learning · Reinforcement learning

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1 Introduction

In this section, an introduction and motivation of the problem we are analyzing and solving is presented, together with a description of the state of the art and an explanation of the paper structure.

1.1 Motivation and Background

Mobile networks nowadays provide much more sophisticated services and are becoming more and more complex. The demanded high quality of the services requires an optimal utilization of the networks resources. Typical for modern mobile networks is the implementation of a multi-radio access technology (multi-RAT) scenario. This is the simultaneous operation of RATs and infrastructure concepts from different generations, such as global system for mobile communications (GSM), universal mobile telecommunications system (UMTS) and long term evolution (LTE) [1]. Deploying state of the art and upgrading legacy technologies and solutions for mobile networks should be straightforward and possible with minimal need of decommissioning old services or changing the physical topology of network elements, such as base stations (BS) [1].

The environment in a mobile network changes constantly and dynamically, which leads to variations in the coverage area of the cells. Reasons for these changes in the network are the exponential growth of traffic over the years [2], variable traffic load, dynamical radio propagation conditions, malfunction of BSs, insertion or deletion of one or more BSs, errors made in the network planning phase, etc. In addition to this, users are mobile and their spatial and temporal distributions are uneven, thus hotspots occasionally could occur in densely populated urban areas. Therefore, as technologies and user demands evolve, the network performance should be scalable and much higher throughput should be provided. However, manual optimization of the network performance is a highly complex and time and cost consuming task for mobile operators [1].

In order to make the network more autonomous, the 3rd generation partnership project (3GPP) has introduced the concept of self-organizing networks (SON) as a step towards achieving fully cognitive networks and autonomic networking in the future [1]. Part of the SON use cases define coverage and capacity optimization (CCO) for 4th generation mobile networks. One of the CCO use cases has been identified for automatic optimization of network resources and its main objective is to provide sufficient coverage and capacity in the whole network area with minimum radio resources. This CCO use case is further divided to three sub-objectives maximizing the relative coverage in the area so that continuous coverage is achieved [1]. The relative coverage is defined as the probability that the received SINR is better than the minimum required, thus providing a sufficient quality of service (QoS) in terms of achievable bit rate, over the entire area and maximizing the system capacity in terms of bit rate.

One means for optimizing the capacity and coverage provided by a BS is steering the tilt angle of its antenna. Tilting is possible both mechanically and electrically, but usually the latter is utilized for coverage and capacity optimization [3].

Depending on the current network environment, number of users, their distribution and the high-level goals of the mobile operator, best trade-off between coverage and capacity for the network can be achieved. High-level goals or policies of the operator are determined by the prioritization of capacity over coverage or vice versa. Such optimization can be utilized for example when a hotspot of users is formed in between different cells. If one

BS is serving the users in the hotspot and they are close to it, it can adjust its antenna tilt towards them. This would lead to a stronger received signal for the users in the hotspot and if the neighboring BS also adjust their tilts, the interference from other cells would be reduced, thus improving the SINR.

For example, in a high-dense urban area with many business buildings, the offices should be well covered during business work hours. The restaurants and canteens nearby should be covered during lunch and dinner time, resulting in a change in the tilt of the nearby BS antennas. Outside of working hours, the homes of the users should get better coverage, while during the weekends, places for entertainment, such as shopping malls, cinemas, parks and restaurants shall be well covered. Such distributions of users are strongly correlated as they are repeatable and in time, on a weekly, daily or even hourly basis. Additionally, each user has different throughput requirements for the particular services he wants to use and a specific behavior, which also varies in time.

These patterns in location and behavior can be learned from the network and utilized in the future to predict user location and demands. Thus, the antenna tilts could be adjusted in advance, so that the network has a proactive response to the environment. Therefore, self-optimization of the antenna tilt is considered very important for the performance enhancement of current and future networks.

In this paper, a method to provide predictive and adaptive means of optimizing the tradeoff between the coverage and capacity of a mobile network in a timely manner is proposed. Based on this, an algorithm acting in a self-organized way, contributing also to the self-optimization and self-healing functions of the network, is developed. The algorithm relies on real-time measurements, key performance indicators (KPIs) and statistically collected data from the network elements and user terminals. For solving the problem in an autonomous and predictive way, the proposed algorithm utilizes methods defined in machine learning and more specifically—reinforcement learning (RL).

The proposed solution can be applied to counteract issues like insufficient coverage at the cell borders (coverage holes), excessive interference (pilot pollution), or weak signals received by the users. The optimization procedures are designed in such a way, that they can be combined with other self-organizing functions and features, to facilitate, for example, load balancing, interference coordination and power allocation. This way, a holistic approach to the coordination between the different SON features can be utilized. The solution can be integrated with novel concepts in mobile networks such as additional vertical or horizontal sectorization.

Current practical implementations of CCO techniques in mobile networks are limited. Benefits from applying the proposed solution are enhanced network performance and service quality as well as reduction of qualified manual effort for optimization of the antenna tilt. The effectiveness of the solution is illustrated through simulation experiments. Based on the results, the algorithm provides significant gain in the overall throughput of the network, as compared to no antenna tilt optimization. The applied machine learning algorithm is model-independent. Therefore, the solution can be applied to mobile networks in general, independent of their generation, technologies, standards or the way the network is realized.

The described idea and method for CCO of a mobile network utilizing antenna electrical tilt have the potential to offload regular optimization tasks from the mobile network operators. Such tasks are delegated to qualified engineers and require manual effort, hence they are expensive, time-consuming and repeatable [1]. Moreover, as human resources are limited, the reduction of costs for operation, administration and maintenance (OAM) of the network is a major goal for the mobile operators.

From a technical perspective, the quality of network operation could be enhanced if such an optimization solution is deployed. Coverage and capacity can be dynamically and predictively optimized, depending on the geographical distribution of the users and their momentary throughput demands. If shorter optimization time periods are implemented, in the order of minutes, the network can dynamically and adaptively (or even predictively and proactively) provide capacity to hotspots or cover effectively areas when poor signal reception occurs.

The presented solution improves throughput, guarantees the minimum data rate required by the user and enhances the mobile services in general. As a result, the quality of experience (QoE) for the users is improved and usage of more and diverse services is stimulated, which contributes to the revenue from network operation.

1.2 State of the Art

In [4], the authors focus on the self-optimization of remote electrical tilt from the perspective of CCO. Simulation studies are performed for best-effort traffic and resource fair scheduling by using LTE snapshot simulator where propagation and uneven user distribution are modeled in three dimensions for a realistic macro-cellular network scenario. Coverage and capacity optimization by means of adaptive remote electrical tilt (RET) adjustment is mainly discussed and the results are given in terms of different performance indicators. It is shown that RET optimization may provide significant performance improvement in case of suboptimal network planning or reuse of 3G network planning.

In [5], the adaptation of antenna tilt angle is formulated as an optimization task aiming for utility fairness. Namely, the objective is to jointly adjust antenna tilt angles within the cellular network so as to maximize user utility, subject to network constraints. Adjustments at BS are carried out jointly in a coordinated manner in order to manage interference. This optimization problem is nonconvex, but the authors show that under certain conditions, it can be reformulated as convex. Specifically, they show that: (1) in the operating mode with high SINR and with an appropriate choice of variables, the optimization is convex for any concave utility function; and (2) in any SINR regime, the optimization can be formulated in a convex manner when the objective is a proportional fair rate allocation. The approach in [5] is lightweight, making use of measurements that are already available at base stations, and is therefore suited to distributed implementation. However, this optimization model is correct only under certain conditions, whereas the algorithm proposed in the current paper functions with no such constraints.

In [4], a centralized optimization algorithm on the basis of case based learning (CBL) is proposed. This method relies on the storage of cases or instances in a memory and applies them directly in new situations. CBL is an appropriate technique because of its low complexity in implementation and high accuracy in case of small number of training examples and irrelevant features. In CBL, all numeric feature values are linearly normalized and k-nearest neighbor algorithm is used as a prediction function [4]. An overview of the CBL algorithm proposed in [4] is made in [6]. According to this overview, a limited number of training examples are collected from the network by a central server and stored in memory. These training examples are measurements (e.g., received power, SINR, call drops) and they are applied to new states of the network. The optimum antenna tilt is then determined using the k-nearest neighbor algorithm where the case that closely matches the current state is chosen. Although [4] does not state what the minimum number of training examples should be, different sets of examples would have to be collected for different network environments.

In [6] the authors apply a RL based Sparse Sampling algorithm for the coverage self-optimization through antenna tilting. According to this research, this algorithm is better than supervised learning and Q-learning based algorithms, as it has the ability to adapt to network environments without prior knowledge, handle large state spaces, perform self-healing and potentially focus on multiple coverage problems. The paper focuses on the problem of coverage self-optimization in the context of LTE networks by adjusting the antenna tilt.

In [7], the proposed method for self-optimization of the tilt angle is based on fuzzy RL techniques and operates in a fully distributed, asynchronous and autonomous fashion without any need for a priori information for the network conditions or any human interventions. The solution is shown to be capable of handling extremely noisy feedback information from mobile users, as well as being responsive to the changes in the environment, including self-healing properties. The simulation results confirm the convergence of the solution to the global optimal settings and that it provides up to 20 % performance improvement when compared to an existing fuzzy logic based RL approach. The CCO in [7] is done using a Fuzzy RL approach, namely Q-learning, which is a technique where the entire state space is searched to find the optimum solution. Since the cellular network environment can possibly be in infinite states or configurations, this number is drastically reduced in [7] through fuzzification, followed by optimization done in a distributed manner. Although the fuzzification step has the advantage of reducing the state space and the noise, it reduces the flexibility of the algorithm and its ability to focus on multiple coverage problems [6]. But the algorithm also does not introduce significant throughput gain.

The RL sparse sampling algorithm in [6] also overcomes the problems of the algorithms used in [4] and [7], namely, the inability to adapt to network environments without prior knowledge and the inability to handle a large set of network configurations. A centralized architecture is adopted and the algorithm is shown to have self-optimizing and self-healing capabilities.

From an architecture perspective, in [6] the authors focus their work in the context of LTE networks, however they have implemented a centralized approach. This means, that there is one agent per cell site that implements the algorithm, and a master agent that decides which agents get to act simultaneously. A design choice has been made wherein the master agent allows only non-conflicting or non-overlapping cells to act simultaneously. Only the first-tier neighbors of a cell are assumed to be conflicting. Nevertheless, such an assumption might not be very appropriate if an urban environment is considered as in the current work. In contrast to [6], a distributed architecture is selected in our scenario.

A centralized approach is also implemented in [4]. It is declared that this strengthens the analysis of the basic cause of the problem (e.g., capacity vs. coverage, excessive uptilting or downtilting) and selects the cells to be optimized with dedicated weighting parameters for prioritization as well as avoiding the changes in the parameters of cells which may interact with each other.

Nevertheless, because of the inconsistent radio propagation characteristics of the different cells in the network and the variation of geographical distribution of traffic load across the cells, it is recommended that the downtilt adjustment is performed in a distributed fashion on a cell-by-cell basis and that the solution is responsive to the environment changes. Compared to the centralized tilt angle optimization, it is shown that the cell-based scheme can provide significantly more gain [7].

The proposed method in this work contributes with adding dynamic and adaptive tilt adjustment, based on RL methodology with low computational complexity for distributed real-time operation. In comparison with other research works, which consider either no learning and/or only static network environment, and/or static user distribution, we consider the mobile network to be a dynamic environment adaptive to current user distributions. This means that based on a learning algorithm, the network can predict the optimal antenna tilts for a particular user distribution. The learning approach does not depend on the model, reduces the signaling and does not need information about future user distributions and their probabilities.

1.3 Structure of the Paper

The rest of the paper is structured as follows. Section 2 describes the system model, formulates the problem and elaborates on how we model the antenna radiation pattern and mobile radio channel. The proposed RL solution is explained in Sect. 3. The basic principles of RL and a flowchart of the algorithm are presented also there. Simulation results are provided, described and evaluated in Sect. 4. Finally, in Sect. 5, we conclude the paper and recommend future research directions on the topic.

2 Problem Formulation

In this section, we describe the system model, formulate the problem and show how the antenna radiation pattern and mobile radio channel are modeled.

2.1 System Model

We consider a mobile network in an urban environment as shown in Fig. 1 and assume that each base station is equipped with three antennas, each covering one sector. From a practical perspective, this assumption corresponds to typical mobile network deployments as the BS serves users inside its sector. Further, the term cell is used with the same meaning

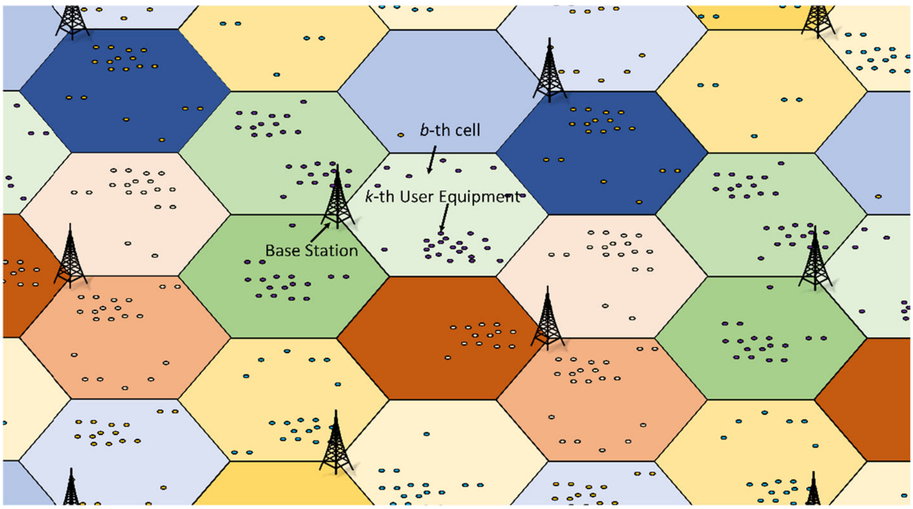

Fig. 1 Model of the mobile network

as sector. We assume that each cell can be geometrically approximated as a hexagon, thus the network is multicellular and sectorized. In practice, due to inconsistent radio propagation characteristics and uneven environment landscape, the shape of the cell is not a perfect hexagon.

The user equipment (UE) or user terminals are randomly distributed in the network. It could happen that some UEs are not covered by any cell and they can get no service. The analysis in this paper focuses on the radio signals transmitted by the BS and received by the UE, i.e. the downlink of the cellular system.

Let B denote the number of cells and K denote the number of UEs in the network. We assume that the transceiver power for each BS antenna is constant and is the same for all the base stations in the network. We suppose, that the b-th base station antenna, $b = \{1, \ldots, \mathrm{B}\}$, transmits signal $s(t)$ with power P_{T}, as shown in Fig. 2.

The signal is amplified with the gain of the BS antenna, denoted as $G_{\mathrm{T}(k,b)}(\theta_b)$. It propagates through the wireless channel between the b-th BS antenna and the k-th UE, $k = \{1, \ldots, \mathrm{K}\}$. The path loss and shadowing are expressed with the channel gain between the UE and the BS antenna $|h_{k,b}|^2$. We consider additive channel noise $n(t)$ and interference $i(t)$. The channel noise and internal UE noise is approximated as additive white Gaussian noise (AWGN), i.e. with constant power spectral density (PSD) and power P_{N}. The period of optimizing the antenna tilt angle is in the order of hours, hence, short-term channel variations, such as fast fading, are omitted in the analytical model.

The k-th UE receives the signal $r(t)$ from the b-th BS antenna with power $P_{R(k,b)}$, which depends on the gain of the BS antenna in the downlink $(G_{\mathrm{T}(k,b)})$, the gain of the UE antenna in the uplink $(G_{\mathrm{R}(k,b)})$, the transmit power (P_{T}) and channel gain $(|h_{k,b}|^2)$

$$P_{\mathrm{R}(k,b)} = P_{\mathrm{T}} \cdot G_{\mathrm{T}(k,b)} \cdot G_{\mathrm{R}(k,b)} \cdot |h_{k,b}|^2. \tag{1}$$

A more detailed definition of the channel gain $|h_{k,b}|^2$ is given in Sect 2.4.

We assume that each UE is equipped with an omnidirectional antenna, which has a constant gain of one in all directions, i.e. $G_{\mathrm{R}(k,b)} = 1$. Therefore, $G_{\mathrm{R}(k,b)}$ is omitted in the next equations.

In order to maintain the work concise, the system design described here implements a simplified path loss and shadowing model, which captures the essence of signal propagation in an urban environment. These effects are expressed with the channel gain $|h_{k,b}|^2$, which is also a dimensionless quantity.

We assume a frequency reuse factor of one, meaning that the system is limited by the interference from neighboring cells and not by the received noise. Therefore, for determining the data rate offered to UE k by cell b, the SINR is decisive. It is expressed as

$$\gamma_{k,b} = \frac{P_{\mathrm{R}(k,b)}}{P_{\mathrm{N}} + P_{\mathrm{I}(k)}}, \tag{2}$$

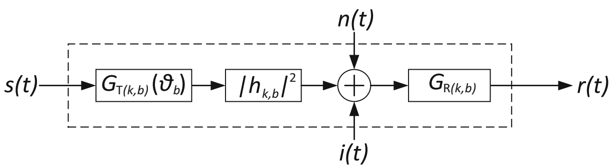

Fig. 2 Model of the mobile radio channel

where the term $P_{\mathrm{I}(k)}$ is the power of the interfering signals $i(t)$ received at k and transmitted by all cells, other than b

$$P_{\mathrm{I}(k)} = \sum_{l=1, l \neq b}^{B} P_{\mathrm{R}(k,l)}. \tag{3}$$

The data rate with which UE k is served by cell b can be expressed using the Shannon–Hartley theorem [8] as

$$R_k[\mathrm{bit/s}] = \Delta f \cdot \log_2\left(1 + \gamma_{k,b}\right), \tag{4}$$

where Δf is the frequency bandwidth of the transmitted signal $s(t)$ and R_k is in bits per second. We assume that we have divided the available bandwidth in N_{sc} subcarriers by using multicarrier transmission, such as orthogonal frequency-division multiplexing (OFDM) applied in LTE and WiMAX [1]. Then Eq. (4) can be generalized as

$$R_k = \sum_{n=1}^{N_{\mathrm{sc}(k)}} \frac{\Delta f}{N_{\mathrm{sc}}} \cdot \log_2\left(1 + \gamma_{k,b,n}\right), \tag{5}$$

where $N_{\mathrm{sc}(k)}$ is the number of subcarrier frequencies allocated to user k and $\gamma_{k,b,n}$ is the SINR for the n-th subcarrier. For simplicity, we assume that each user is assigned a single subcarrier.

In order to achieve a higher data rate for user k, we have to maximize the SINR $\gamma_{k,b}$ and $P_{\mathrm{R}(k,b)}$ and to minimize the interference $P_{\mathrm{I}(k)}$, according to (2), (3) and (5). For a snapshot of the network in the time domain, we assume that for particular and static BS and UE the channel gain $\left|h_{k,b}\right|^2$ and the BS transceiver power P_{T} are fixed. Thus, we can alter the BS antenna gain G_{T} in order to maximize the received SINR.

2.2 Modeling the Radiation Pattern of BS Antenna

In this subsection, the problem of how to accurately model the radiation pattern of the antennas at the BS will be introduced. This is important for CCO, because the proposed solution adjusts the antenna tilt in order to optimize capacity and coverage.

Antenna tilt is defined as the angle between the direction of the main beam of the antenna pattern and the horizon. In Fig. 3, a BS with its antenna is depicted, as seen from the side (cross section with the vertical plane). The main, side and back lobes of the antenna radiation pattern, as well as the vertical beamwidth and tilt angle parameters, are depicted. The total tilt angle is shown as θ_{tilt} and consists of two angles—mechanical and electrical. Fundamentally, downtilting is possible both mechanically and electrically [3]. In mechanical downtilt, antenna main lobe is lowered on one side and the antenna back lobe is raised on the other side because antenna elements are physically directed towards the ground (see Fig. 4a). In Fig. 4a, the mechanical downtilt angle is denoted by $\theta_{\mathrm{mechanical}}$.

For an antenna at the BS in a mobile network, an antenna array of dipole elements is extensively used [9]. In electrical downtilt, the main, side and back lobes are tilted uniformly (see Fig. 4b). This is achieved by adjusting the phases for each of the antenna array elements [3]. In Fig. 4b, the electrical downtilt angle is denoted by $\theta_{\mathrm{electrical}}$. The total tilt angle is

$$\theta_{\mathrm{tilt}} = \theta_{\mathrm{mechanical}} + \theta_{\mathrm{electrical}}. \tag{6}$$

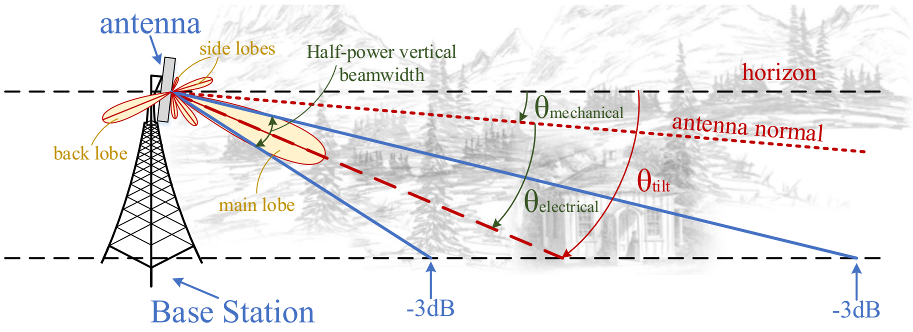

Fig. 3 A base station and one of its antennas. The main, side and back lobes of the antenna radiation pattern, as well as the vertical beamwidth and tilt angle parameters, are denoted

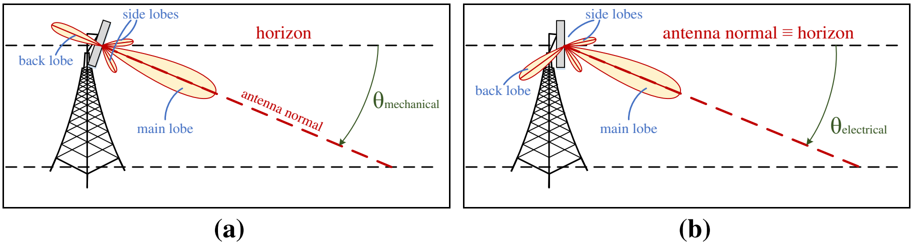

Fig. 4 Mechanical downtilt (**a**) and electrical downtilt (**b**)

when the antenna is downtilted towards the ground, then the change in angle is positive. If the antenna is uptilted, then the change in angle is negative [6]. In Fig. 3, the antenna is downtilted, which means that the tilt is positive, $\theta_{\mathrm{tilt}} > 0°$. Figures 3 and 4 show cross sections of the antenna radiation pattern with the vertical (elevation) plane. The azimuthal plane is the one which is perpendicular to the elevation plane and parallel to the direction of the main beam of the antenna.

Adjusting the mechanical downtilt requires site visits, which are time and cost inefficient and inflexible. The advances in electrical downtiliting have enabled remote adjustment of radiation pattern for all azimuth angles by means of signal phasing alteration. Novel techniques enable intelligent algorithms to be employed for autonomous configuration and optimization of the downtilt angles and remove or minimize the need for expensive drive testing and statistical analysis of network performance and fault reports [7]. Therefore, the antenna is usually tilted mechanically during the installation and initial setup of the network. Afterwards, the fine-tuning adjustments of the tilt are carried out utilizing the electrical tilt.

In the following, we show how the BS antenna gain G_{T} can be adjusted with the change of the antenna tilt angle. For the bth BS antenna, in our notation, the combined antenna tilt angle θ_{tilt} is denoted as θ_b. When $\theta_b > 0°$, the antenna is downtilted towards the ground. If $\theta_b < 0°$, the antenna is uptilted away from the ground.

Theoretically, the radiation pattern of an ideal BS antenna is not a simple function of the tilt angle θ_b. In order to facilitate the modelling and simulations of next generation mobile networks, 3GPP has proposed a simplified antenna radiation pattern in [10]. Most of the published works, which are aiming to solve the problem of autonomous capacity and coverage optimization, use this approximation model. According to it, the antenna attenuation in the horizontal (azimuthal) plane for a 3-sector cell site is expressed as

$$A_{\mathrm{H}}(\varphi) = -\min\left[12\left(\frac{\varphi}{\varphi_{3\mathrm{dB}}}\right)^2, A_{\mathrm{m}}\right], \text{ [dBi]}, \tag{7}$$

where $\varphi, [^\circ]$ is the angle between the normal to the antenna and the direction of measurement, $\varphi_{3\mathrm{dB}}, [^\circ]$ is the horizontal half power beamwidth (HPBW) of the main lobe and $\mathrm{A_m}$, [dBi] is the attenuation with which the side and back lobes of the pattern are approximated. It must be noted that in practice, usually the back lobe of the antenna pattern has less attenuation as compared to the side lobes. These parameters apply to the azimuthal (horizontal) plane. The antenna attenuation in the vertical plane is

$$A_{\mathrm{V}}(\theta, \theta_b) = -\min\left[12\left(\frac{\theta - \theta_b}{\theta_{3\mathrm{dB}}}\right)^2, SLA_{\mathrm{v}}\right], \text{ [dBi]}, \tag{8}$$

where $\theta, [^\circ]$ is the angle between the normal to the antenna and the direction of measurement, $\theta_{3\mathrm{dB}}, [^\circ]$ is the vertical HPBW of the main lobe and SLA_{v}, [dBi] is the attenuation of side lobes of the antenna pattern. These parameters apply to the vertical (elevation) plane. $\theta_b, [^\circ]$ represents the tilt angle of the antenna with respect to the horizon. Typically, $\varphi_{3\mathrm{dB}} = 70^\circ$, $\mathrm{A_m} = 25$ dBi, $\theta_{3\mathrm{dB}} = 10^\circ$ and $\mathrm{SLA_v} = 20$ dBi [10].

Finding the antenna attenuation in any point in space can be analytically expressed by combining (7) and (8)

$$A(\varphi, \theta, \theta_b) = -\min\{-[A_{\mathrm{H}}(\varphi) + A_{\mathrm{V}}(\theta, \theta_b)], A_{\mathrm{m}}\}, \text{ [dBi]}. \tag{9}$$

In order to obtain the antenna gain in a certain point in space, the maximum antenna gain $G_{\mathrm{T,max}}$, [dBi] should be added to (9)

$$G_{\mathrm{T}}(\varphi, \theta, \theta_b) \text{ [dBi]} = A(\varphi, \theta, \theta_b) + G_{\mathrm{T,max}}. \tag{10}$$

The maximum antenna gain is technology and vendor specific. The operating frequency also influences the antenna gain [11]. Typically, $G_{\mathrm{T,max}}$ is in the order of 15 dBi [10, 11]. Equation (10) shows, that the gain of the BS antenna depends on the angles φ, θ and θ_b. φ and θ are determined by the relative position of the BS and UE. Hence, for a static snapshot of the mobile network, these angles can be considered as fixed. However, by tuning the tilt angle θ_b, the antenna gain can be adjusted, i.e. $G_{\mathrm{T}}(\theta_b)$.

In [3], [5] and [12] it is confirmed, that the pattern defined by [10] is suitable for practical and theoretical modelling of the vertical pattern of antennas, deployed in today's mobile networks.

2.3 Problem Statement

The objective of this work is to maximize the user satisfaction by adjusting the tilt angle of the BS antennas in a mobile network. Let us assume, that the kth user demands a certain data rate $\tilde{R}_k$. One of the means for achieving maximum user satisfaction is to ensure that the throughput for each of the UE reaches at least its corresponding demanded rate $\tilde{R}_k$. Therefore, we can postulate the objective function as

$$\sum_{k=1}^{\mathrm{K}} w_k \cdot \left(\tilde{R}_k - R_k\right), \tag{11}$$

where $R_k \equiv R_{k,b}$ is the data rate received by the k-th user. w_k is a weighting factor which determines the user priority and $0 \leq w_k \leq 1$. The closer to 1 is w_k, the priority of the user is higher and will achieve higher data rate. Higher values can be assigned to users, which are more distant to the cell or are located in poor radio conditions and therefore can have lower data rate. If $w_k = 0$, then the satisfaction of the k-th user is neglected. Such low value can be used when an UE is close to the BS antenna and receives higher than the demanded data rate.

As the electrical tilt can be altered remotely and therefore used to optimize the network performance predictively, the optimization problem aims to minimize (11) by adjusting the tilt angle and can be postulated as

$$\begin{gathered} \underset{\Theta}{\operatorname{argmin}} \sum_{k=1}^{\mathrm{K}} w_k \cdot \left(\tilde{R}_k - R_k(\Theta)\right) \\ \text{subject to } \theta_{b,\min} \leq \theta_b \leq \theta_{b,\max}, \end{gathered} \tag{12}$$

where $\Theta = (\theta_1, \ldots, \theta_b, \ldots, \theta_{\mathrm{B}})$ is a vector, containing the tilt angle of each BS in the network. The weighting factor can be set to $w_k = 0$ for users, for which $R_k(\Theta) > \tilde{R}_k$, and to $0 < w_k \leq 1$ otherwise. This way, satisfied users will not be taken into consideration for the optimization. The limits of the electrical tilt angle are chosen to be $\theta_{b,\min} = 0°$ and $\theta_{b,\max} = 10°$, as in practical antennas [1].

It must be noted that the optimization problem (12) is non-convex and therefore cannot be easily solved with standard optimization techniques.

2.4 Modeling the Mobile Radio Channel

Considering only the path loss, the mobile radio channel gain in an urban environment $\left|h_{k,b}\right|^2$ corresponds to

$$\left|h_{k,b}\right|^2 = \left(\frac{\lambda}{4 \cdot \pi \cdot d_0}\right)^2 \cdot \left[\frac{d_0}{d_{k,b}}\right]^{\alpha}, \tag{13}$$

where $d_{k,b}$ is the distance between BS antenna b and UE k, as shown in Fig. 5.

d_0 is a reference distance for the antenna far-field and α is a path loss exponent.

According to the definitions in [8], the scenario modelled in this work is an urban macrocell environment, hence $\alpha = \{3, 7, 6, 5\}$.. Due to the scattering phenomena in the antenna near-field, model (13) is generally only valid at transmission distances $d > d_0$, where d_0 is typically assumed to be $(1 - 10)$m indoors and $(10 - 100)$m outdoors. λ is the radio wavelength used for signal transmission and depends on the signal frequency

$$\lambda = \frac{\mathrm{c}}{f}, \ [\mathrm{m}], \tag{14}$$

where $\mathrm{c} \approx 3 \times 10^8 [\mathrm{m/s}]$ is the velocity of radio wave propagation, which in free space is equal to the speed of light; f, [Hz] is the frequency of the transmitted signal.

In (1), $P_{\mathrm{R}(k,b)}$ is a mean value, which is averaged over any random variations due to shadowing in the mobile channel. In addition to path loss, the signal typically experiences

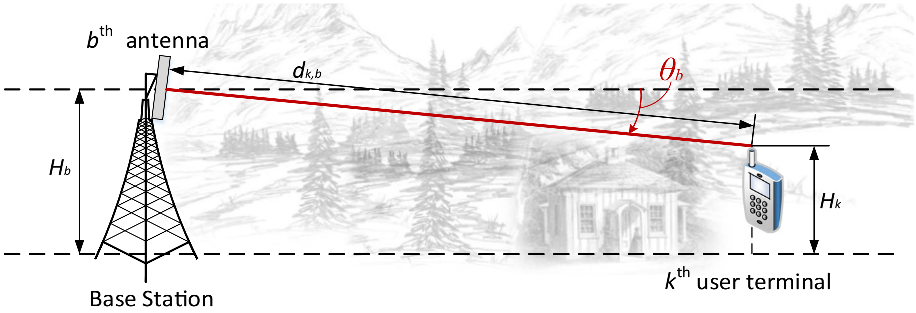

Fig. 5 A base station with the bth antenna and the kth user terminal. Antenna heights are also denoted: H_b for the BS and H_k for the UE

random variation due to objects in the signal path, giving rise to a random variation of the path loss at a given distance. Changes in reflecting surfaces and scattering objects can also cause random variation of the path loss, therefore a model for the random attenuation due to these effects is implemented. Since the location, size, and dielectric properties of blocking objects, as well as the changes in reflecting surfaces and scattering objects that cause the random attenuation, are generally unknown, statistical models are widely used to characterize this attenuation. The most common model for this additional attenuation is log-normal shadowing. This model has been confirmed empirically to accurately model the variation in path loss (channel gain) or received power in both outdoor and indoor radio propagation environments. In the log-normal shadowing model, the channel gain $|h|^2$ is assumed random with a log-normal distribution, given by [8]

$$p\left(|h|^2\right) = \frac{\xi}{\sqrt{2\pi}\sigma_{\psi_{\mathrm{dB}}}|h|^2}\exp\left[-\frac{\left(10\log_{10}|h|^2 - \mu_{\psi_{\mathrm{dB}}}\right)^2}{2\sigma^2_{\psi_{\mathrm{dB}}}}\right], \quad |h|^2 > 0, \tag{15}$$

where $\xi = 10/\ln 10$, $\mu_{\psi_{\mathrm{dB}}}$ is the mean of $\psi_{\mathrm{dB}} = 10\log_{10}|h|^2$ in [dB] and $\sigma_{\psi_{\mathrm{dB}}}$ is the standard deviation of ψ_{dB}, also in [dB]. When the channel gain is log-normally distributed, the received power $P_{\mathrm{R}(k,b)}$ is also log-normal. The mean of $|h|^2$ (the linear average path loss) is [8]

$$\mu_{|h|^2} = E\left[|h|^2\right] = \exp\left[\frac{\mu_{\psi_{\mathrm{dB}}}}{\xi} + \frac{\sigma^2_{\psi_{\mathrm{dB}}}}{2\xi^2}\right]. \tag{16}$$

The conversion from the linear mean (in [dB]) to the log mean (in [dB]) is [8]

$$10\log_{10}\mu_{|h|^2} = \mu_{\psi_{\mathrm{dB}}} + \frac{\sigma^2_{\psi_{\mathrm{dB}}}}{2\xi}. \tag{17}$$

The distribution of the ψ_{dB} value is Gaussian with mean $\mu_{\psi_{\mathrm{dB}}}$ and standard deviation $\sigma_{\psi_{\mathrm{dB}}}$ [8]. The standard deviation $\sigma_{\psi_{\mathrm{dB}}}$ is used to generate channel gain variations in the current work. Incorporating shadow (slow) fading, the channel gain can be expressed as

$$|h_{k,b}|^2 = \left(\frac{\lambda}{4\cdot\pi\cdot d_0}\right)^2 \cdot \left[\frac{d_0}{d_{k,b}}\right]^{\alpha} \cdot \psi_{k,b}, \tag{18}$$

where the dimensionless coefficient ψ is a log-normal distributed random variable. It can be derived from

$$\psi = 10^{\frac{\psi_{\mathrm{dB}}}{10}}, \tag{19}$$

where ψ_{dB} is a normal distributed random variable with mean zero and variance $\sigma^2_{\psi_{dB}}$. Substituting (1), (2), (3) and (18) in (5), we get

$$R_k = \sum_{n=1}^{N_{\mathrm{sc}(k)}} \frac{\Delta f}{N_{\mathrm{sc}}} \cdot \log_2\left(1 + \frac{P_{\mathrm{T}} \cdot G_{\mathrm{T}(k,b)} \cdot \left(\frac{\lambda}{4 \cdot \pi \cdot d_0}\right)^2 \cdot \left[\frac{d_0}{d_{k,b}}\right]^{\alpha} \cdot \psi_{k,b}}{P_{\mathrm{N}} + \sum_{l=1, l \neq b}^{\mathrm{B}} P_{\mathrm{T}} \cdot G_{\mathrm{T}(k,l)} \cdot \left(\frac{\lambda}{4 \cdot \pi \cdot d_0}\right)^2 \cdot \left[\frac{d_0}{d_{l,b}}\right]^{\alpha} \cdot \psi_{l,b}}\right), \left[\frac{\mathrm{bit}}{\mathrm{s}}\right]. \tag{20}$$

Here $d_{k,b}$ and $d_{l,b}$ express the transmission distances between the UE and the respective BS antennas. Similarly, $\psi_{k,b}$ and $\psi_{l,b}$ are log-normally distributed random variables for modelling the shadow fading.

3 Reinforcement Learning Solution

In this section, the proposed RL solution is explained. First, the key idea, basic principles and application of RL to our scenario are explained. Then, the architecture of the solution and representation as a Markov decision process are described. The section concludes with a definition of the reward function and flowchart of the algorithm.

The problem defined in the previous section is non-convex and therefore is hard to be solved with standard optimization techniques in real time. However, a ML approach, with a solution implementing Reinforcement Learning RL can be applied for the autonomous optimization of the BS antenna tilt angles. RL is suitable for application to the considered problem, because it has relatively low computational complexity and avoids the “trial and error” nature of some other ML techniques. This is important for mobile networks, because failure in the network operation is highly undesirable.

3.1 Idea and Basic Principles of RL

According to [13], in RL the training and testing phases are intermixed. To collect information, the learner actively interacts with the environment and in some cases affects the environment, and receives an immediate reward for each action. The object of the learner is to maximize its reward over a course of actions and iterations with the environment. No long-term reward feedback is provided by the environment, hence the learner is faced with the exploration versus exploitation dilemma, since it must choose between exploring unknown actions to gain more information versus exploiting the information already collected [13].

In the scenario of the stated problem, the agent is the cell site and it observes the environment (or network) through the measurements it collects. In RL, an agent acts on the environment and learns based on what it observes. If the agent performs an action at time t, it causes the environment to go into state s_{t+1} (see Fig. 6). RL requires mapping that state to a reward r_{t+1} and by observing that reward, the agent knows if it has performed a good or a bad action. The agent’s behavior is a sequence of observations, actions and rewards for those actions. Over time, the agent learns to perform the right action, given a particular

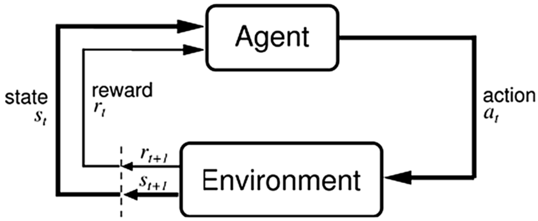

Fig. 6 The reinforcement learning framework: agent-environment interaction [14]

state [6]. The agent's goal is to maximize the total amount of reward it receives over the long run [14]. The agent-environment interaction, described above, is shown in Fig. 6 [13].

3.2 Application of RL for Solving the Current Problem

For the case of self-optimization of antenna tilt, the learner is the instance of an algorithm, whether it will be distributed in the BSs or in a centralized unit in the network. The environment consists of the UEs, the tilt angle of the BS antenna, other BSs, the conditions of the radio link between the BS and the UE.

The context of the developed RL solution is based on what data is available at each BS: the relative distance d to each of the served UEs (the delay time for the signal propagation to reach the UE is known); the power of the received UE signal $P_{\mathrm{R}(k,b)}$; the interference from other cells $P_{\mathrm{I}(k)}$; the weighting factors w_k for each UE.

3.3 Architecture of the Solution

The first generations of mobile communications systems, including GSM (second generation, 2G) and UMTS (third generation, 3G), did not implement communication between BSs. However, in LTE such communication was implemented with the X2 interface between BSs (evolved NodeBs). It is used to facilitate the signaling between BSs and to enhance system performance. Hence, it is foreseen that such communication will also be implemented in future mobile systems.

Therefore, for the presented solution, a distributed architecture with coordination and communication between the BSs is chosen. The algorithm is executed in each BS. The BSs communicate with each other and coordinate their actions. Nevertheless, because the learning algorithm is independent of the model, the idea can be applied to older generations of mobile networks as well, but with a centralized architecture.

In most practical mobile network deployments, when a centralized Operations, Administration and Management (OAM) system is implemented, it could be used to provide high-level goals for the trade-off between capacity and coverage to each BS and to coordinate actions between different BSs. In addition, such a centralized element as the OAM system enhances the scalability of the solution, as the complexity of distributed decision-making grows with the number of elements in the system.

The distributed approach has inherent redundancy, being a distributed system. The mutual coordination between the BSs and between the OAM system and each BS avoids concurrency issues in the distributed system, such as oscillations, race conditions and deadlocks. Practically, the solution is considered to be responsive to changes in the environment [1].

3.4 Representation as a Markov Decision Process: States and Actions

The idea and working principles of the developed method can be represented by a Markov decision process (MDP). States are mapped to the current antenna tilt angle setting and the transition between different states means that the tilt angle has changed. The state-action diagram can be generalized, as shown in Fig. 7. The states are $s_l \in S$. If the action to keep state s_l active is denoted with m_l, then the possible actions are $m_l \in \mathcal{A}(s_l)$. Transitions between any two states are possible, therefore the state-action diagram is fully interconnected. The mapping of the states to the antenna tilt angles can for example be the following: s_0 corresponding to $\theta_b = \theta_{b,\min}$, s_1 to $\theta_b = 1^\circ$, $s_{(S-1)}$ to $\theta_b = \theta_{b,\max}$. In such a case, the step for changing the tilt is $\Delta\theta_b = 1^\circ$. From practical point of view, most of the antennas currently deployed in mobile networks enable tilt adjustment with such a step. A model with six states, a step of $\Delta\theta_b = 2^\circ$ and possible states $S = \{0^\circ, 2^\circ, 4^\circ, 6^\circ, 8^\circ, 10^\circ\}$ is implemented in the simulation tests, results from which are presented in the sections below.

3.5 Reward Function and Matrix

For each action m_l it takes, the agent receives a reward R_l. The reward is bigger if the number of users whose demand is satisfied is greater, which means that the overall capacity and coverage have been enhanced. The reward function can be expressed as

$$R_l = \mu \cdot S + \eta \cdot U, \tag{21}$$

where S is the sum data rate for all users of the cell, which is normalized to the cell capacity, that can be achieved with the allocated frequency resources in an interference-free (noise-limited) environment. U is the number of satisfied users in the cell and it is normalized to the potential total number of served users inside the cell. For this purpose, the algorithm needs to have information of the user distribution in the network, which is obtained by the relative distance d to each of the users, based on the delay time for the signal propagation to reach each of the users.

The coefficients μ and η give the priority for the trade-off between capacity and coverage. For example, if $\mu > \eta$, the optimization will aim to achieve higher throughput, for less users in the network. Similarly, for $\mu < \eta$, more users will be covered, but the average throughput will be lower.

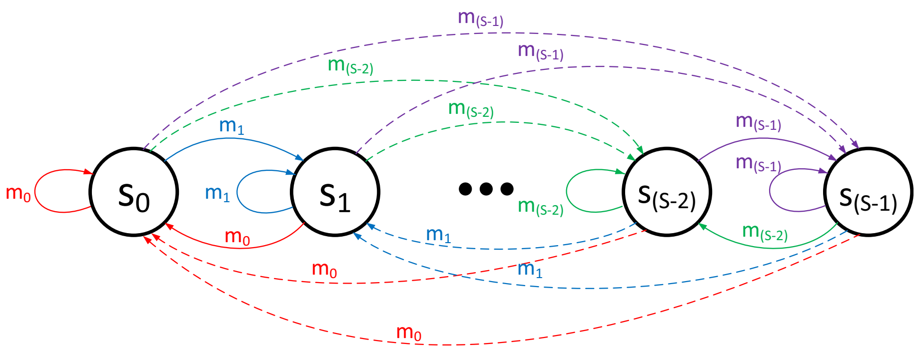

Fig. 7 Generalized state-action diagram. States are $s_l \in S$, possible actions are $m_l \in \mathcal{A}(s_l)$

Table 1 Generalized reward matrix

Action					
State	m_0	m_1	$\cdots$	m_{s-2}	m_{s-1}
S_0	$\boldsymbol{R}_0$	$\boldsymbol{R}_1$	$\cdots$	$\boldsymbol{R}_{s-2}$	$\boldsymbol{R}_{s-1}$
S_1	$\boldsymbol{R}_0$	$\boldsymbol{R}_1$	$\cdots$	$\boldsymbol{R}_{s-2}$	$\boldsymbol{R}_{s-1}$
...	...	...		...	...
S_{s-2}	$\boldsymbol{R}_0$	$\boldsymbol{R}_1$	$\cdots$	$\boldsymbol{R}_{s-2}$	$\boldsymbol{R}_{s-1}$
S_{s-1}	$\boldsymbol{R}_0$	$\boldsymbol{R}_1$	$\cdots$	$\boldsymbol{R}_{s-2}$	$\boldsymbol{R}_{s-1}$

Based on the rewards for each action, a Reward Matrix (RM) is constructed. It maps the reward R_l, received for being in state s_l and taking action m_l. An exemplary generalized RM is shown on Table 1 and in (22).

$$\boldsymbol{R} = \begin{bmatrix} R_0 & R_1 & \cdots & R_{S-2} & R_{S-1} \\ R_0 & R_1 & \cdots & R_{S-2} & R_{S-1} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ R_0 & R_1 & \cdots & R_{S-2} & R_{S-1} \\ R_0 & R_1 & \cdots & R_{S-2} & R_{S-1} \end{bmatrix}. \tag{22}$$

3.6 Flowchart of the Algorithm

The basic idea and principles of the developed method for CCO, utilizing the BS electrical antenna tilt, are illustrated with a flowchart of the algorithm and a simplified version in Fig. 8.

The described algorithm is for the b-th BS antenna or b-th cell. In the initial phase the optimization starts with exploring all of the possible tilt angles s_l from the state space S. The setting of the tilt angle can be done either randomly or with a prediction for the most optimal state. During the simulation tests, both methods were implemented. For simplicity, the final solution presented here uses random state selection. Although the convergence time of the two methods is almost the same, state selection based on prediction is generally better suited for practical implementation in real mobile networks.

The time interval for exploration of each tilt angle setting is in the order of hours. Throughout this time, statistical data is collected related to the network performance and received data rate by each user in the cell. Based on this data, the respective reward R_l. is calculated using (21). A reward matrix $\boldsymbol{R}$ is constructed where the values for the received rewards are filled in. Following the biggest reward in $\boldsymbol{R}$ is found. As a result, the corresponding tilt angle is the optimal one for the current user distribution and radio propagation environment.

After exploring all of the states, follows the exploitation phase of the algorithm, where the optimal tilt angle is set until the next iteration of the algorithm. During this time, for example 24 h, statistics are collected and the reward matrix is periodically updated.

In the next time step, the current network performance is compared with the stored performance data and the tilt angle may be predictively tuned to optimize the capacity and coverage for the current user distribution and radio propagation environment.

A detailed flowchart of the algorithm is illustrated in Fig. 9a–c. It represents the work of the network as a whole and adds more steps to the logic described above. After the

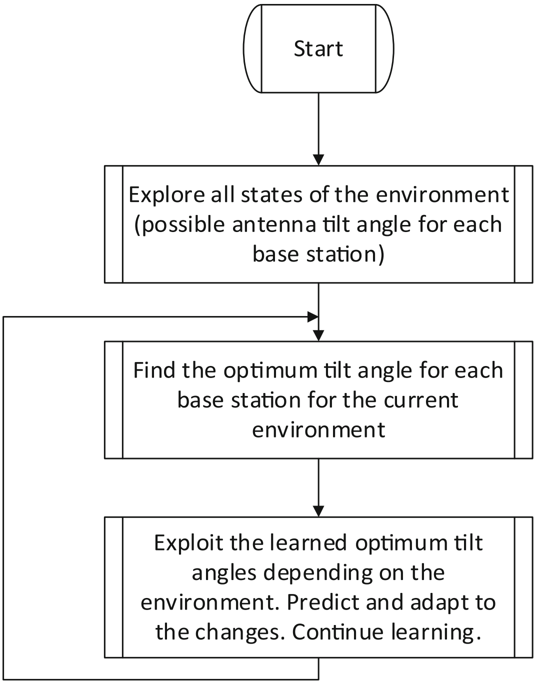

Fig. 8 Flowchart of the simplified algorithm for capacity and coverage optimization, utilizing the base station electrical antenna tilt

initialization of the algorithm, a check for available statistical data is made. If the collected performance data is sufficient, the algorithm enters directly into the exploitation phase. If the data is not enough, the exploration phase is started.

In this phase all the B BS antennas are optimized, but not simultaneously. If the number of BS in the network is large, a suitable approach is to do the optimization on a per cell cluster basis. This means, that cells are optimized in clusters, one cell at a time. A cluster is a group of cells, formed by a central cell and all of its first-tier neighbors. This way, the interference from other cells and respectively the received SINR are kept constant. The different clusters are optimized in parallel, so that the convergence time is relatively low. It is assumed, that the cells, other than those in the current cluster, are located too far away to cause significant interference and therefore they can be optimized separately. This assumption is valid in general for urban macrocells.

After the exploration phase, the algorithm enters the exploitation phase. If no optimization is needed or there is not enough statistical data collected, it is stopped until the next time step. If there is a need of optimization and sufficient amount of statistical data is obtained, the tilt angle of each of the BS antennas is optimized on a per-cluster basis using prediction for the optimal angle.

The reward R_l is computed and saved in the reward matrix $\boldsymbol{R}$. Statistical data is collected until the next time step after which the algorithm enters in the next iteration and continues to operate in a similar manner.

If a problem is detected at any step of the algorithm, it is reported to the central OAM system and its execution is interrupted.

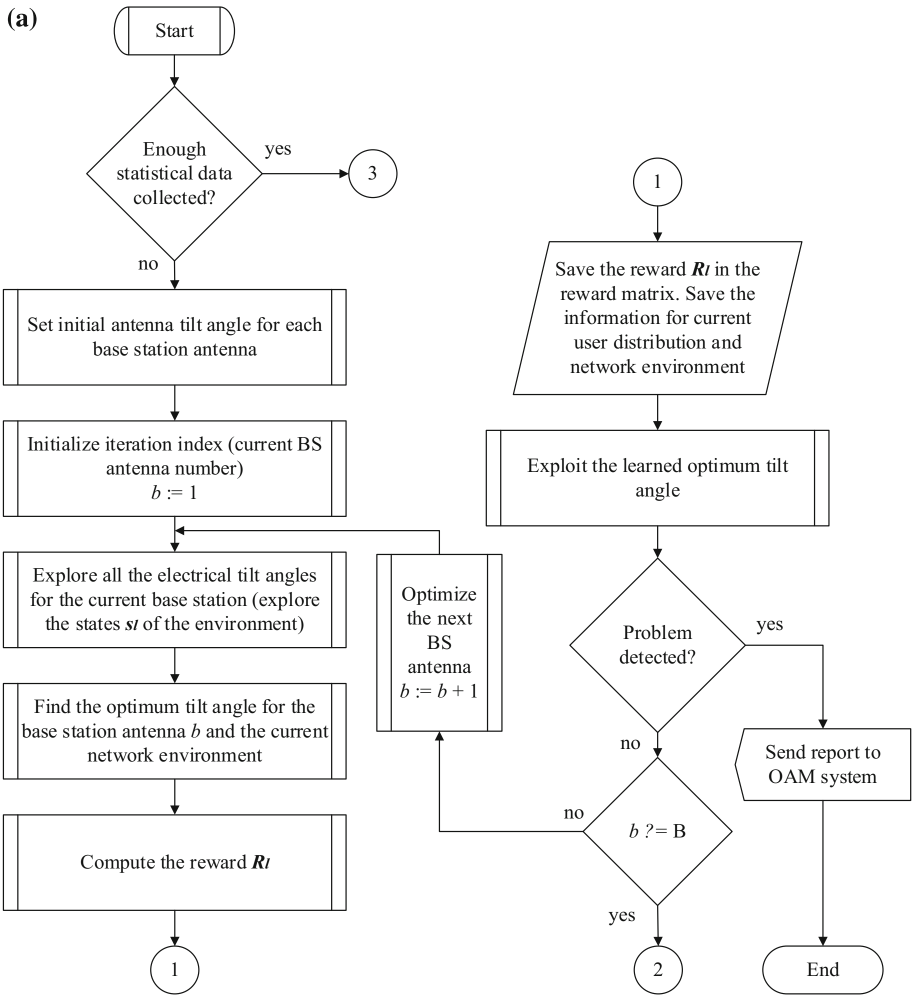

Fig. 9 Flowchart of the algorithm for CCO, utilizing the BS electrical antenna tilt

4 Performance Evaluation and Results

In this section, we provide, describe and evaluate the results of simulation tests of the proposed solution. Based on the algorithm presented in Sects. 2 and 3, a simulation model was developed in the MATLAB computing environment, version 2013b.

4.1 Simulation Parameters and Environment

The antenna parameters, which are used for implementing the solution, are shown in Table 2. The main simulation parameters are listed in Table 3.

Based on the parameters in Table 2, the plots of the vertical pattern $A_{\mathrm{V}}(\theta, \theta_b)$ for $\theta_b = 0°$, $\theta = \{-180°, 180°\}$ and of the horizontal pattern $A_{\mathrm{H}}(\varphi)$ for $\varphi = \{-180°, 180°\}$ in polar coordinates are shown in Fig. 10.

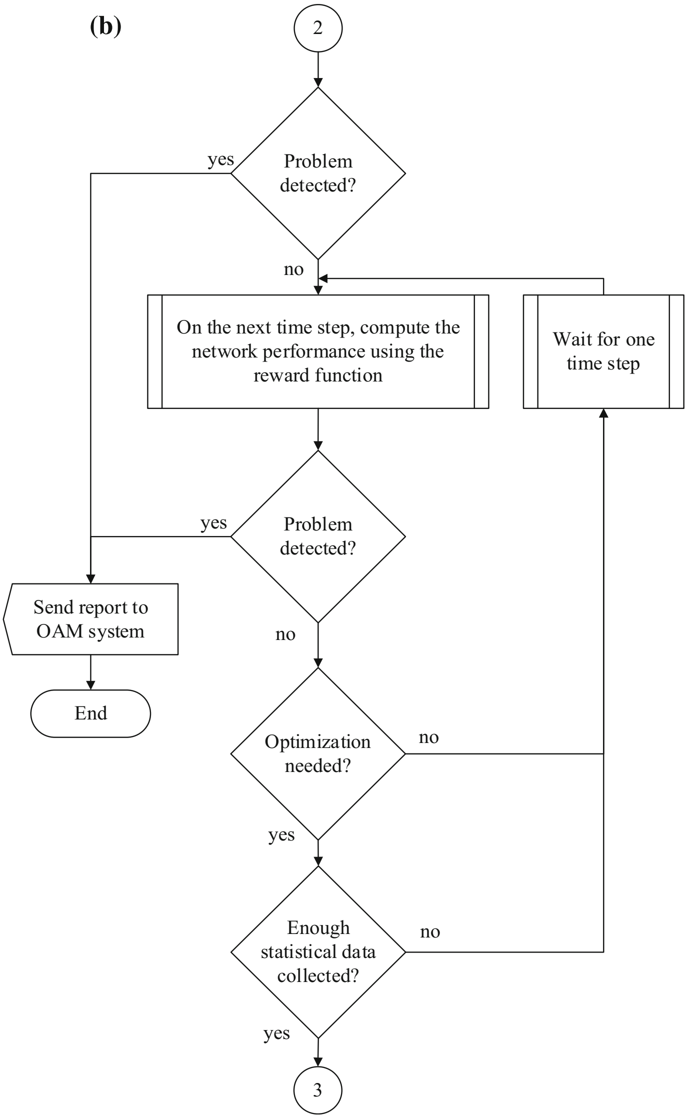

Fig. 9 continued

4.2 Simulation Results

In this subsection, the results from simulations of the proposed solutions are described and evaluated.

The first stage of implementing and testing the model consists of modelling a simple cell site with three sectors (three cells) and a simplified channel. The goal is to show the basic operation of the algorithm. Each of the sectors is covered by one antenna. The three antennas are directed at $0^\circ, 120^\circ$ and 240°, respectively. At 0°, the main beam of the

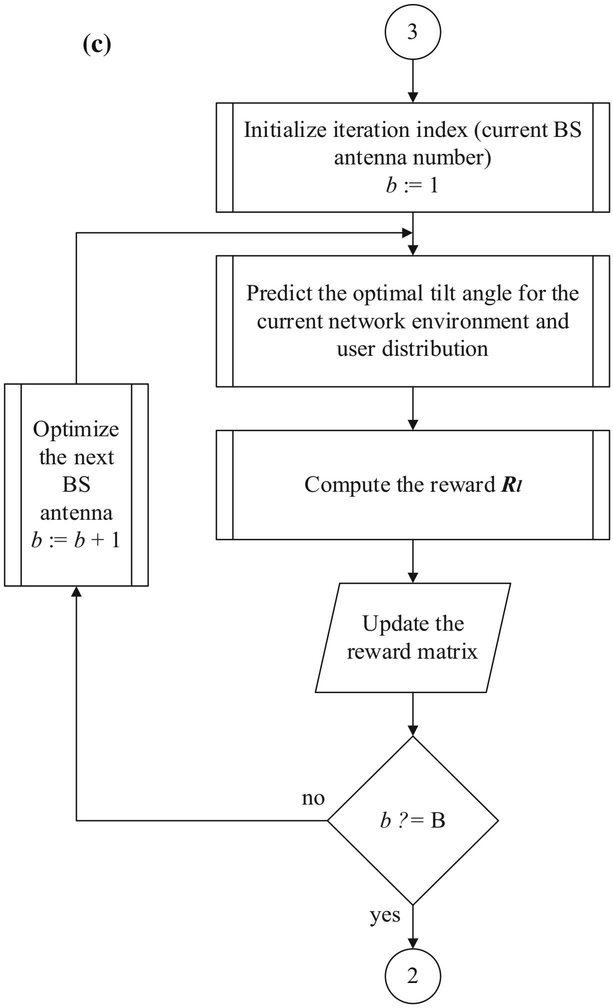

Fig. 9 continued

antenna pattern points towards the X axis. The angle increases with a counterclockwise rotation. The initial electrical tilt angle for each of the BS antennas is set to $\theta_b = 6^\circ$ for $b = \{1, 3\}$. In practice, this is a common value for urban BS deployments.

In the beginning, for simplicity the simulation tests are conducted with three users, distributed within the network, assuming no shadowing and fast fading. The radio propagation characteristics are modelled for free-space transmission, meaning that the path loss exponent in (13) is set to $\alpha = 2$. No inter-cell interference is considered. The user locations and the network are assumed constant and static in time. The dimensions of the simulated network are 10 km by 10 km. The BS antennas are placed at the coordinate origin.

The power of the received signal by a user is computed for the whole network with a geometrical step of 10m in both the X and Y directions. The samples are plotted on a map of the received power, $P_{\mathrm{R}(k,b)}$ (1). The received power map before initializing the

Table 2 Antenna simulation parameters

Parameter	Symbol	Modeling	Value	Dimension
Horizontal antenna radiation pattern	$A_{\mathrm{H}}(\varphi)$	According to (7), [10]	–	dBi
Horizontal HPBW	$\varphi_{3\mathrm{dB}}$	According to [10]	70	°
Maximum horizontal attenuation	$\mathrm{A_m}$		25	dBi
Vertical antenna radiation pattern	$A_{\mathrm{V}}(\theta, \theta_b)$	According to (8), [10]	–	dBi
Vertical HPBW	$\theta_{3\mathrm{dB}}$	According to [10]	10	°
Vertical side lobe attenuation	$\mathrm{SLA_v}$		20	dBi
Minimum electrical tilt angle	$\theta_{b,\min}$	According to [4]	0	°
Maximum electrical tilt angle	$\theta_{b,\max}$		10	°
Step of electrical tilt adjustment	$\Delta\theta_b$	–	2	°
Combined 3D antenna pattern	$A(\varphi, \theta, \theta_b)$	According to (9), [10]	–	dBi
Maximum antenna gain	$G_{\mathrm{T,max}}$	–	14	dBi
Transceiver power for each BS antenna	$P_{\mathrm{T,dBm}}$	According to [10]	46	dBm
	P_{T}		≈40	W
BS antenna height	H_b		32	m
UE antenna gain	$G_{\mathrm{R}(k,b)}$	According to [4]	0	dBi
UE antenna height	H_k	According to [10]	1.5	m

Table 3 Main simulation parameters

Parameter	Symbol	Modeling	Value	Dimension
Carrier frequency	f	–	2600	MHz
Frequency bandwidth	Δf	According to [10]	10	MHz
Number of subcarriers	N_{sc}	–	5000	–
Number of subcarriers, allocated to user k	$N_{\mathrm{sc}(k)}$	–	1	–
Frequency reuse factor	FR	According to [4]	1	–
Path loss exponent	α	According to [8]	4.5	–
Shadow fading standard deviation	$\sigma_{\psi_{dB}}$	According to [4]	8	dB
SINR threshold for service availability	$\gamma_{\min}$	–	15	dB
Maximal working temperature	$T_{\max}$	–	25	°C
Call duration	Δt_{call}	–	60	s

optimization algorithm is shown in Fig. 11. The user locations are represented with asterisks (*) and are numbered. The cells are denoted by their indexes and their approximate borders illustrated with white dashed lines.

The received power map results after completing the exploration phase of the algorithm are presented in Fig. 12. From these results can be concluded, that cells 1 and 3 have tilted their antenna angles upwards. The reason for this is the current user distribution. As we can observe from these two figures, user 1 is located at the origin, user 2 is near the border between cells 1 and 3 and user 3 is near the edge of cell 3. Because user 1 is very close to the antennas, it receives a signal with relatively high power. User 2, being near the cell border, does not have so good reception before the optimization. Hence, cell 2 is uptilted to provide higher received power to user 2. Similar is the case for user 3 and therefore cell 3 is also uptilted from 6° to 2°. Cell 2 is serving no users. Hence, it is downtilted to

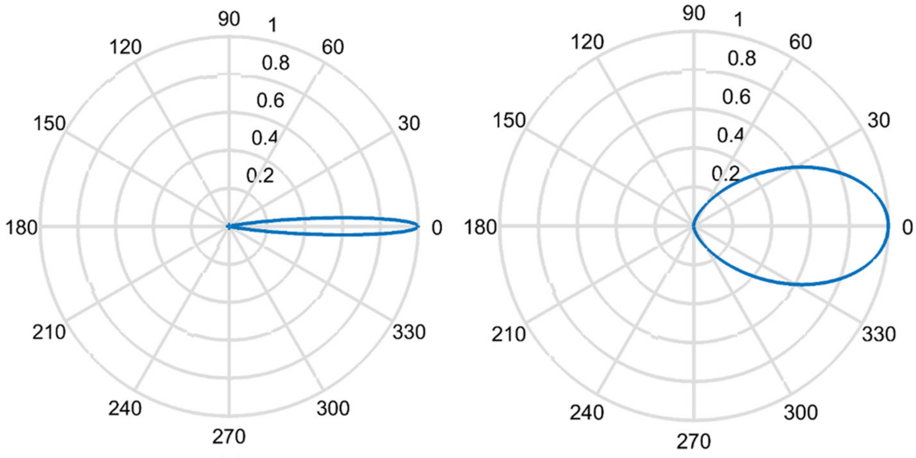

Fig. 10 **a** Antenna vertical pattern $A_V(\theta, \theta_b)$ for $\theta_b = 0°$, $\theta = \{-180°, 180°\}$ in polar coordinates; **b** antenna horizontal pattern $A_H(\varphi)$ for $\varphi = \{-180°, 180°\}$ in polar coordinates

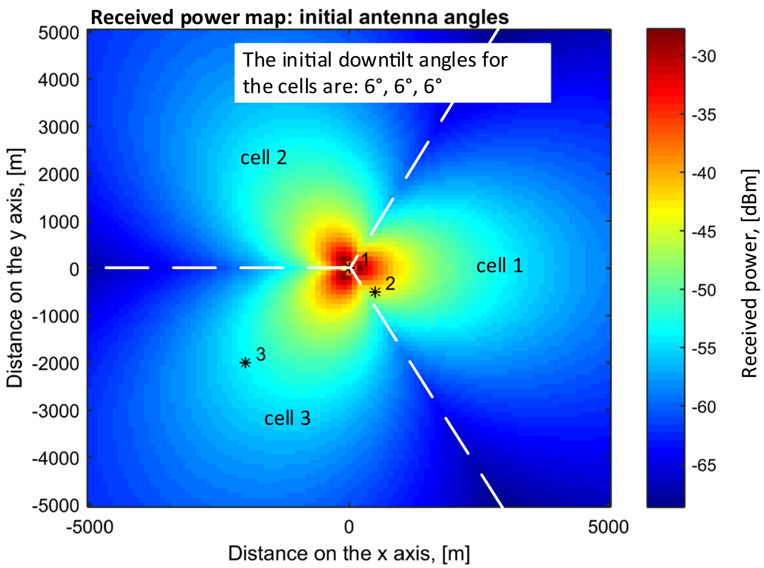

Fig. 11 Simple network scenario: received power map before initializing the optimization algorithm

$\theta_{b,\max} = 10°$. This downtilting policy can be modified, but is chosen in order to reduce the interference to adjacent cells. The states through which the antenna tilt angle changes for cells 1 and 3, are illustrated in Fig. 13. The mapping between states and tilt angles is

$$s_1 = 0°, \quad s_2 = 2°, \quad s_3 = 4°, \quad s_4 = 6°, \quad s_5 = 8°, \quad s_6 = 10°. \tag{23}$$

This number of states and relatively coarse tilt adjustment step $\Delta\theta_b$ are chosen in order to reduce the complexity of the simulations and to show the functionality and effectiveness

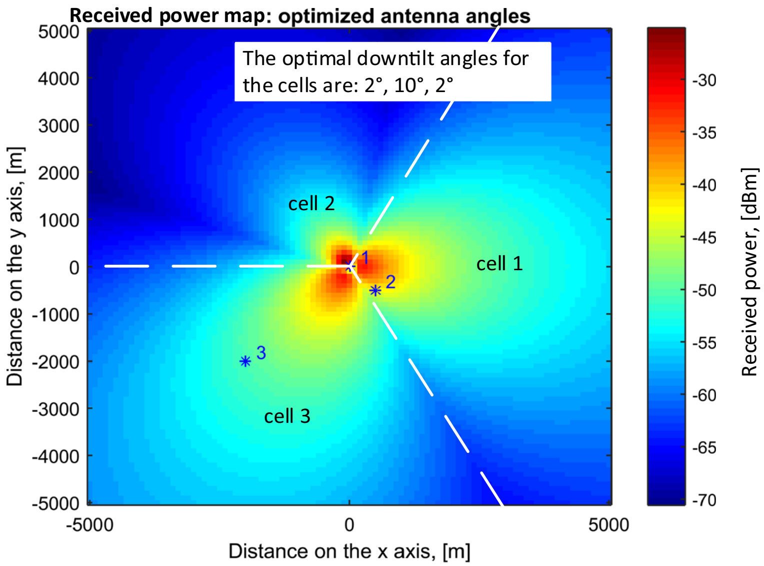

Fig. 12 Simple network scenario: received power map after completing the optimization algorithm

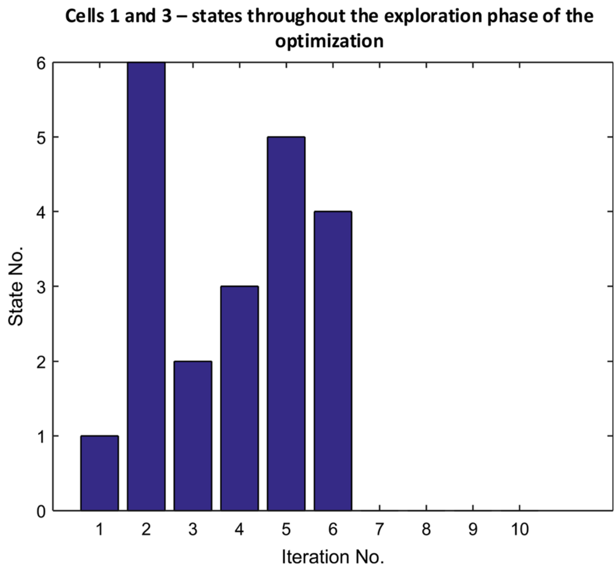

Fig. 13 States during the exploration phase for cells 1 and 3

of the method. In this first stage of development, the state to be explored is selected based on prediction for the possible rewards.

The algorithm explores consecutively all possible states for each of the cells. The initial state of each antenna is s_4. An empty reward matrix is created starting with cell 1. The first state selected is s_1, therefore the antenna electrical tilt angle is set to 0°. The received reward is computed and the RM updated. Then the algorithm explores the next most-distant state to the already explored one, which means s_6. Hence, it downtilts the angle to 10°. Because the received reward in this state is smaller than the received for the previous action, the previous state, s_1, is marked as near-optimal. The closest unexplored state to the near-optimal state is selected next, i.e. s_2. The received reward is so far the highest, so s_2 is now marked as near-optimal.

In a similar manner, in the next iterations, the unexplored states are selected. After all tilt angles have been explored and the reward matrix has been constructed, the action with biggest reward is reproduced. Hence, the optimal tilt angle is set. With this action, the exploration phase completes. It is executed again for the next cells in the cluster, in this case three times in total. Because cell 2 serves no users, it is directly downtilted to 0°. A similar simulation test was performed for the same network scenario with more randomly distributed users in the network and with similar results.

As a next step, shadow fading and radio propagation characteristics for urban environment were implemented in the model and inter-cell interference was considered. The simulation results after completing the exploration phase of the algorithm for a network with three cells and three users, whose locations are assumed constant and static in time, are shown in Fig. 14. The dimensions of the simulated network are 1km by 1km and the computational step is 1m. This reduction of the size of the cells is due to the higher influence of path loss and fading, as compared with the previous examples. User locations are represented with asterisks (*). The cells are denoted by numbers and their borders are illustrated with dashed lines. The data rate for each of the three users is shown in Table 4. As it can be seen from the results, user 2 (located near the border between cells 1 and 2)

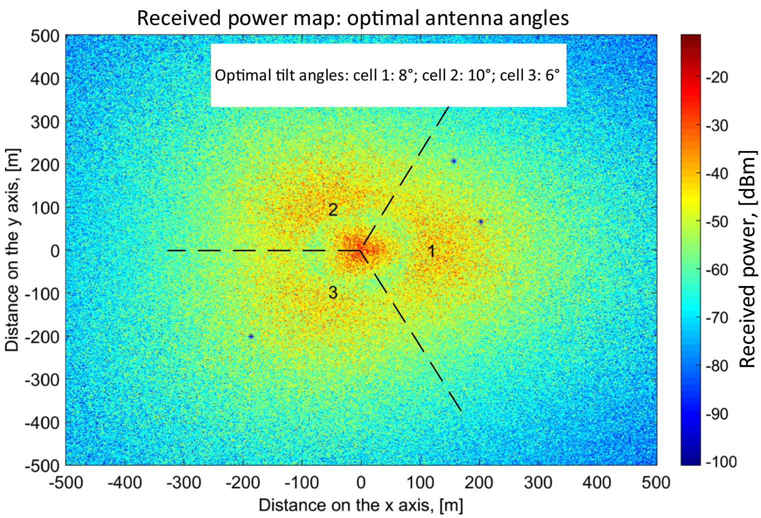

Fig. 14 Received power map after optimization of 3 cells and 3 randomly distributed users

Table 4 Simulation results for a network with 3 cells and 3 randomly distributed users

Data rate [bit/s]	User 1	User 2	User 3	Sum rate for the network [bit/s]
Before tilt optimization	12,436.59	0.00	6965.57	19,402.16
After optimization	13,446.30	5049.23	7159.97	25,655.50

receives low SINR and therefore has no service. After tilt optimization, user 2 receives sufficient SINR and is covered. The sum rate for the network is around 32.2% higher after the optimization. With a scenario consisting of more cells and users, a similar improvement is achieved.

Following simulations for a network consisting of 15 cells and 30 randomly distributed users were conducted. The dimensions of the network are 5 by 5 km and the computational step is 5 m. The received power map after optimization and approximate cell borders are illustrated in Fig. 15. In order to minimize the interference between adjacent cells and to maximize the received SINR, most of the BS antennas are additionally tilted down to 10° from the initial 6°.

It could be shown that a practical deployment of the solution would not be too complex and will require rather insignificant changes in the network. A preliminary calculation shows, that for a deployment in a small exemplary mobile network consisting of 5000 base stations, the invested capital expenditures (CAPEX) will be returned as additional revenue in less than three years of network operation, maintaining optimal network operation.

5 Conclusions and Future Work

In this paper, we propose a novel approach for self-optimization in mobile networks utilizing the BS antenna tilt. To illustrate the approach, we developed an RL based algorithm and simulated its application in an urban scenario. Based on the simulation parameters listed in Tables 2 and 3, the simulation results show around 30% of improvement in the sum data rate of the network after applying antenna tilt angle optimization. The proposed machine learning algorithm is model-independent and can be

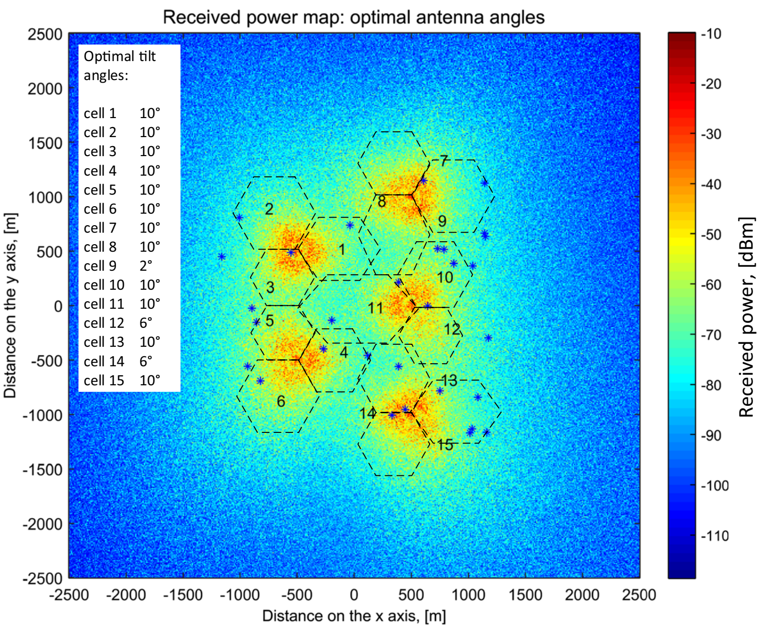

Fig. 15 Received power map after optimization of 15 cells and 30 users, distributed randomly in the network. Approximate cell borders

applied to current and next generations of mobile networks, contributing to the self-organizing functions of the network, for energy saving, inter-cell interference coordination, load balancing, etc. The achievement of a synergistic effect for the network OAM and improvement of network performance, while reducing operational costs, energy consumption and needed resources is expected as a result of the application of the algorithm.

It must be mentioned that in this work only the exploration phase of the developed algorithm is described. As the system operates and collects statistics, it learns based on experience. This knowledge consists of previous user distributions and demands. Hence, it can be utilized to improve the prediction of future geographical distributions of user terminals. When such a prediction is implemented in the exploitation phase, the tilt angle could be adjusted a priori to avoid formation of coverage holes or weak signal reception with insufficient data rate.

The modelled antenna radiation pattern is simplified and follows a technical specification by 3GPP for the LTE technology. For the purpose of evaluating the results against a practically deployed mobile network, a pattern of a real antenna can be used. Example for a widely installed antenna in mobile networks nowadays is given in [11].

For simplification, the number of subcarriers, allocated to user k, $N_{sc(k)}$, is fixed, meaning that all user terminals use the same frequency bandwidth. The simulation model can be further extended by treating the number of allocated subcarriers as a variable, depending on the user data rate demand. In addition, the problem of capacity optimization with different frequency reuse schemes can be studied by evaluating the cell-edge throughput performance. This will tailor the solution to mobile communication systems, which use Frequency-division multiple access (FDMA), such as GSM.

Simulation tests in a network, especially in a realistic urban environment, incorporating user mobility and prediction, are expected also to confirm the effectiveness of the method. The application of the method for the simulation of specific network technologies including detailed models of effects, such as fast fading, will be a subject of future work.

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