Dynamic Coverage Optimization for 5G Ultra-Dense Cellular Networks Based on Their User Densities

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Dynamic Coverage Optimization for 5G Ultra-dense Cellular Networks based on Their User Densities

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Abstract: This paper has proposed a user-density-based coverage optimization technique for ultra-dense cellular networks. Antenna tilting is a promising coverage optimization technique to be used in 5G networks that significantly improve the signal to interference plus noise ratio (SINR) by choosing the appropriate angle of tilt. In this paper, the cellular coverage has been optimized for scattered user densities/user-hotspots using an adaptive antenna tilting mechanism that steers the beams towards the temporal hot spot in the coverage area. The proposed method has the competence to improve the desired SINR level and coverage area for a group of the user rather than a single user. In this work, a reinforcement learning (RL) algorithm has been implemented to optimize the tilt angle. The performance of the proposed technique has been evaluated in the simulation platform considering a three-sectored multicellular mobile network where the groups of user clusters are distributed randomly. The result confirms the improvement in RSS and SINR value in the group of users having high density with maximum user satisfaction.

Keywords: Coverage,QoS, Reinforcement Learning, Antenna Tilt, Mobile Network, User Density, Ultra-dense Network, 5G.

1. Introduction

Current cellular networks are becoming more challenged for the mobile network operator (MNO) due to the proliferation of mobile users and heavy demand for high data rates for advanced applications. Hence, to fulfill the requirements technological advancements in the conventional networks are much more necessary. Due to the advancements, the network becomes more complex with an increase in its deployment expenditures i.e. operational expenditure (OpEX) and capital expenditure (CapEX). So the demanded high data rate and good QoS require an optimal usage of the network resources cost-effectively. Another aspect of mobile network performance also depends on the interference parameter. In a practical cellular network, most of the cell edge users are greatly affected by interference due to its weak received power and low SINR level. To meet the several demand-specific requirements in the next-gen cellular network, various researches have been carried out to optimize the antenna parameters to achieve better SINR and good QoS [1, 2].

As the nature of the cellular network is quite dynamic due to various factors (e.g. dynamic characteristics of the propagation medium, user distribution), it is desired to improve the scalability of the mobile network with increased throughput. It is very much expensive and time-consuming for the MNO to optimize the network performance manually [3]. The 3rd generation partnership project (3GPP) has introduced the concept of self-organizing networks (SON) to make the network autonomous for the future cellular network [3]. For the next-generation cellular networks, the coverage and capacity optimization (CCO) is defined as a part of SON use cases, where some self-executing network parameters are discovered to impart enough capacity and coverage [3]. The corresponding coverage is defined as the probability that, the received SINR level is greater than the threshold value. Hence, a sufficient QoS is provided in terms of downlink received signal power over the total area. Moreover, the future (5G) cellular networks are envisioned to be high ultra-dense and more user-centric where the network will follow the individual user or a group of users (hotspot zone) aiming to provide a high data rate and better QoS[4, 5]. Hence, focusing on the coverage as an essential parameter for the future cellular network, a hardware-based technique commonly known as the antenna tilting approach brings more attention towards it, due to its low complexity and OpEX. Due to the deployment of this technique, a notable increase in the desired SINR level and average throughput within a cell can be perceived in addition to the interference to the other cells can be minimized [4, 5]. In this approach, based on the network environment, propagation medium characteristics, and user distribution, one base station (BS) can adjust its tilt angle to achieve a better trade-off between coverage and capacity.

The work presented in this paper is an adjunct to the method proposed in [6], by taking the advantage of the proposed algorithm and process therein. Here, the analysis is based on the antenna tilt performance for scattered user densities in terms of the SINR and RSS, as these are the salient metrics that are used to determine the coverage probability (CP) and average throughput of a mobile network. An RL-based technique is used to make the antenna tilt more independent and self-optimized. The focus of the work is to improve the coverage area towards the cell with maximum user density in urban areas by using BS electrical antenna tilt and to reduce the exorbitant interference within the network.

The rest part of the paper is organized as: section 2 focuses on the state-of-art, in section 3 the system model and the proposed algorithm with the principle of operation is presented, wherein section 4 the simulation results are analyzed and in section V the conclusion with the future scopes are outlined.

2. State-of-Art

A self-optimized and dynamic antenna tilt approach for the best trade-off between coverage and capacity in cellular networks is proposed in [6]. The proposed method uses an RL algorithm, where the simulation has been carried out by only considering a simplified path-loss model [7]. The simulation result confirms that there is a significant improvement (near about 30%) in the sum data rate of the mobile network that can be obtained with this proposed algorithm. A comparative analysis of the proposed method in [7]with different propagation models is presented in [8]. To solve the coverage and interference problem that arises in LTE networks, a novel self-tuning algorithm to adjust the antenna tilt is proposed in [9]. In this method, the heuristic algorithm has been implemented by two fuzzy logic controllers, where the simulation results show that the SINR value at the cell edge is improved by more than 1 dB causing an increase in the spectral efficiency. Using the existing method as in [6], Samal et al. have proposed a CCO method for suburban areas in [10]. With the application of the proposed algorithm, there is substantial improvement in the SINR level at the cell edge can be achieved. The simulation results also confirm user satisfaction at the cell-edge which nearly equals 80-100%. Berger et al. in [11], have proposed a CCO algorithm where coverage and statistical throughput information are used to construct an objective function to estimate the number of covered and uncovered users of each cell. From the simulation results, a significant improvement in the coverage performance and overall throughput gains can be observed. Razavi et al. have proposed a fuzzy RL-based technique to facilitate self-CCO for LTE networks by using BS antenna downtilt in [12]. The proposed solution is a completely distributed fashion without any additional signaling overhead between LTE BSs [12]. A quantum-inspired genetic algorithm is realized in [13] to solve the antenna positioning problem and also different characteristics are compared with existing algorithms like Population-Based Incremental Learning (PBIL) and Genetic Algorithm (GA) and found robust in many aspects. Fuzzy neural network optimization is proposed in [14] for antennas tilt and transmitted power in a cellular network. Both the cell-edge and center performances are considered for the calculation and it is found the above said RL optimization method is performed better than contemporary technologies. Fuzzy Q-Learning solution based on clustering mechanism is proposed in [15] for cell optimization and capacity hitches where it is found that the proposed mechanism learns much quicker than one agent per snapshot strategy and indicates improved enactment than multi-agent per snapshot policy.

In [16], a precise simulation model is prepared based on machine learning algorithm; deep deterministic policy gradient (DDPG), and Bayesian optimization (BO) to appraise different factors for making the best use of coverage zone and reduces the interference by taking into account the transmitted power and elevation tilt in a wireless network. The two models are also compared which indicates the BO model presenting the substantial potential for optimization of the network coverage and capacity. The differential evolution scheme is utilized in [17] for optimization of tilt and azimuth angles in a comparatively weak and overlapping cell area. A framework is proposed in [18] using machine learning for cell planning in a wireless network which focuses on minimum numbers of BS, antenna pattern, and the cluster planning solution for capacity and coverage. Similarly, machine learning-based antenna design is proposed in [19] to optimize the performance of antenna along with a comparative study with traditional antenna design, and also in [20], a review is presented for antenna design using machine learning. The support vector machine (SVM) is implemented in [21] to solve the conflict like cell interference between two adjacent cells and optimization related to coverage and capacity by considering the different antenna parameters. A tool like the LTE simulator (ns3 LENA) is used to realize the same. SVM (support vector machine) of ML is realized in [22] for optimization in reflect array antenna for space communication. The Stochastic Gradient Descent (SGD) algorithm is proposed in [23] to maximize the coverage in a cellular network which requires less computation compared to the meta-heuristic algorithm. Also, the machine learning-based scheme ISO-SON is proposed and validated in [24] to mitigate the cell coverage and adjacent cell interference in LTE networks. A CCO technique with load balancing among different small cells in a heterogeneous network (HetNet) is jointly implemented in [25]. This proposed solution uses antenna tilt and BS transmitting power as the key parameters for the optimization process. A significant improvement in the throughput along with the increase in the SINR level can be observed from the results. The simulation results also confirm about the load balancing among small cells in HetNet which enhances the effective utilization of available resources.

However, due to the inconsistent nature of the radio propagation of different sectors/cells in the cellular network and due to the random geographic distribution of the traffic across the sectors, it is advised that the adaptation of antenna downtilt can be executed in a distributed fashion for individual sectors. This facilitates the network to be more perceptive towards the dynamic environmental changes. The work presented here, emphasizes more on the adaptive and dynamic antenna tilt adjustment by incorporating RL-based methodology. The proposed model in this work is more predictive in terms of envisioning the optimal tilt angle of a BS for different distributed user hotspots.

3. Problem Formulation & Modeling

3.1 System Model

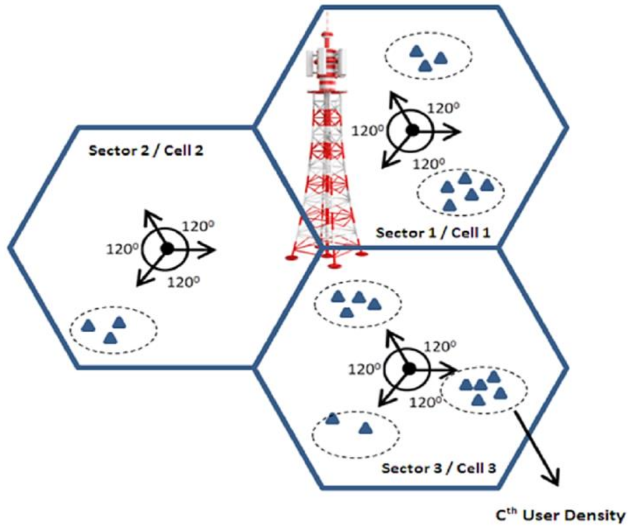


Figure 1: Cellular Network Model

In this work, a mobile network is modeled by considering a sectorized and multicellular network. Assuming each cell is hexagonal in structure and is equally divided into three sectors (the term 'sector' will be referred to as 'cell' in the further part of this paper as the sector and cell carry the same meanings) at an angle of 120°. A single BS mounted with three antennas is placed at the center of the cell, where the user within each sector is served by a single antenna as shown in Figure 1.

This work mainly focuses on downlink (DL) analysis where the RSS is calculated based on the radio signal strength transmitted (P_T) by the BS with antenna gain denoted as $G_{T(n,i)}$, the channel gain $|h_{(n,i)}|^2$ and the distance (d) between the user/user equipment (UE). Here, it is assumed that the users are randomly distributed in such a manner that they form different user densities at different locations within a cell/sector. This proposed model is based on the same scenario and utilizes the algorithm as in [6].

Let's assume that the number of cells in the network is I and as the number of BS is equal to the number of cells, so the i^{th} BS antenna, $i = \{1 \ldots I\}$. Due to the random distribution of the users, C is denoted as the number of user clusters/user densities that are formed within a cell, so the c^{th} user cluster, $c = \{1 \ldots C\}$. The number of users inside each user cluster is denoted as N, so the n^{th} user, $n = \{1, \ldots N\}$.

For c^{th} user cluster-1 the received power (P_R) by n^{th} user,

$$P_{R(n,i)} = P_T G_{T(n,i)} G_{R(n,i)} |h_{(n,i)}|^2 (1)$$

$$P_{R(n,i)}\big|_{c^{th}\text{ User Cluster}} = \sum_{n=1}^{N} P_{R(n,i)} \quad (2)$$

$$SINR_{(n,i)}\big|_{c^{th}\text{ User Cluster}} = \frac{P_{R(n,i)}\big|_{c^{th}\text{ User Cluster}}}{P_N + \sum_{n=1}^{N} P_{I(n)}} \quad (3)$$

Here,P_N = Additive White Gaussian noise (AWGN), $G_{R(n,i)}$ is the gain of the receiving antenna

(Assumed to be equivalent to '1' due to omnidirectional) and $P_{I(n)}$ is the interfered signal power (other than i), received at user n, where$P_{I(n)} = \sum_{l=1,l\neq n}^{N} P_{R(n,l)}$.

The data rate received at the n^{th} user due to the i^{th} servicing BS can be represented by using Shannon–Hartley theorem asfollows (Goldsmith, 2005),

$$R_n(\text{bit/sec}) = \Delta f \cdot \log_2(1 + SINR_{(n,i)}) \quad (4)$$

where, Δf is the bandwidth of the transmitted signal.The channel gain for each user present nearly at equidistance from the BS (i^{th}) in c^{th}user cluster,

$$\left|h_{n,i}\right|^2 = \left(\frac{\lambda}{4\pi d_0}\right)^2 \left[\frac{d_0}{d_{(n,i)}}\right]^{\alpha} \Bigg|_{d_1 \approx d_2 \approx d_3 \ldots\ldots \approx d_N} \quad (5)$$

where,$\lambda$is considered as the wavelength of the transmitted radio signal, $\alpha$is thepath-loss exponent, $d_0$is afar field reference distance of the antenna, and $d_{(n,i)}$ is thedistance of user b from the BS antenna i. $\{$Assuming the Equation (1) is valid only when, $d > d_0\}$

Similarly, as perEquation (2) &Equation (3) the received power and SINR for all user-clusters can be expressed as follows,

$$\left[P_{R(n,i)}\big|_{\text{User Cluster (1)}} = \sum_{n=1}^{N} P_{R(n,i)}\right]$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$
$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$
$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$\left[P_{R(p,i)}\big|_{\text{User Cluster (C)}} = \sum_{p}^{P} P_{R(p,i)}\right]$$

$$\left[\; SINR_{(n,i)}\big|_{\text{User Cluster (1)}} = \frac{P_{R(n,i)}\big|_{\text{User Cluster 1}}}{P_N + \sum_{n=1}^{N} P_{I(n)}}\right]$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$
$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$
$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$\left[SINR_{(p,i)}\big|_{\text{User Cluster (C)}} = \frac{P_{R(p,i)}\big|_{\text{User Cluster C}}}{P_N + \sum_{p=1}^{P} P_{I(p)}}\right]$$

Similarly, by using Equation (4), the channel gain for each user present nearly at equidistance from the BS (i^{th}) in different user clusters can be calculated as,

$$\left|h_{\breve{g},i}\right|^2 = \left(\frac{\lambda}{4\pi d_0}\right)^2 \left[\frac{d_0}{d_{(u,i)}}\right]^{\alpha} \Bigg|_{\breve{g}=\{N,K,L,M,I\ldots\ldots\}\,;\, d_N \neq d_K \neq d_L \neq d_M \neq d_I \neq \ldots\ldots\ldots\ldots} \quad (6)$$

Integrating the shadowing effect and by considering multicarrier transmission, the data rate received by the n^{th} user can be expressed as follows [7],

$$R_{\dot{n}}(\text{bit/sec}) = \sum_{\dot{n}=1}^{N_{sc(\dot{n})}} \frac{\Delta f}{N_{sc}} \log_2 \left\{1 + \frac{P_T G_{T(\dot{n},i)} |h_{(\dot{n},i)}|^2 \, \psi_{\dot{n},i}}{P_N + \sum_{m=1,m\neq i}^{I} P_{R(\dot{n},m)} \, \psi_{m,i}}\right\} \quad (7)$$

Here, $\psi$is considered as lognormal distributed random variable ($10^{\frac{\psi_{dB}}{10}}$).

3.1 Radiation Pattern Modeling of BS Antenna

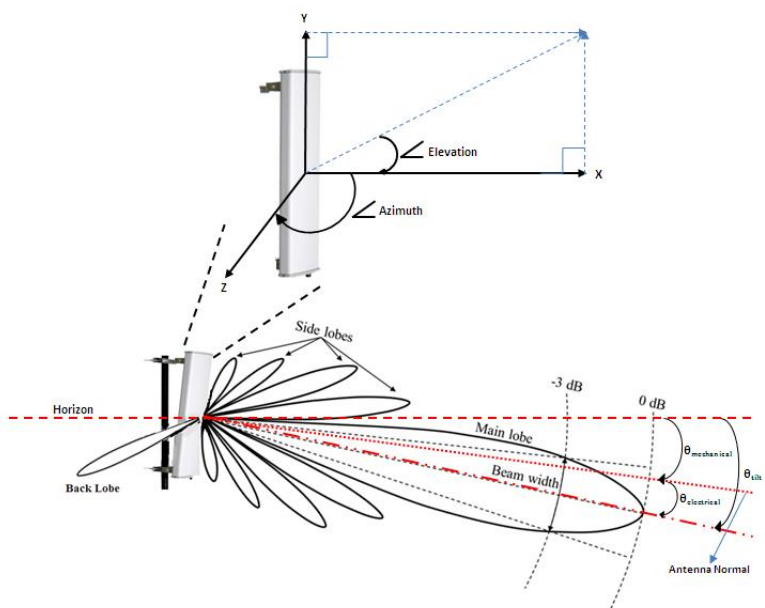


Figure 2: Antenna Tilt Scheme (Electrical and Mechanical) along with the main, back and side lobes of the BS antenna radiationpattern.

To obtain better CCO, it is necessary to adjust the tilt angle of the BS antenna precisely. In general, antenna tilt is commonly referred to as the angle of the main lobe of the radiation pattern of the antenna w.r.t. the horizon. The antenna tilt can be attained in two ways [26], (i) Mechanical Tilt ($\theta_{mechanical}$): where a physical site visit is necessary to adjust the antenna angle (uptilt/downtilt). In mechanical tilt, the front lobe (main lobe) and the back lobe are exactly opposite to each other as they depend upon the position of the antenna dipole elements. (ii) Electrical Tilt ($\theta_{electrical}$): commonly known as Remote Electrical Tilt (RET), which doesn't require any site visit. In RET the front lobe (main lobe), back lobe, and side lobes can be tilted uniformly by altering the phases of each antenna array element [26]. So the total tilt angle (θ_{tilt}) of the BS antenna is,

$$\theta_{tilt} = \theta_{electrical} + \theta_{mechanical} \quad (8)$$

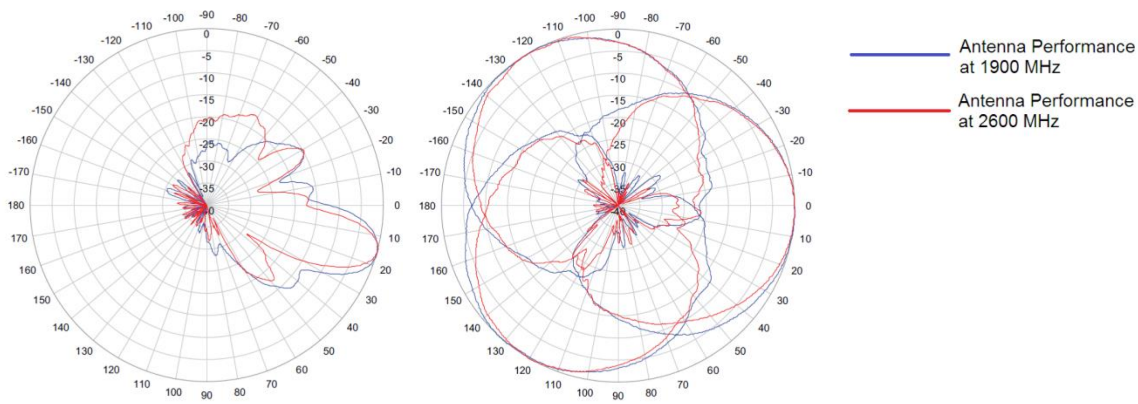
Considering a macro cell with sectorized cell site (tri-sector cell), the vertical radiation pattern $\{A_v(\theta)\}$ and horizontal radiation pattern $\{A_h(\theta)\}$as in [27] can be integrated into a 3-D radiation pattern as,

$$A(\varphi,\theta)|_{dBi} = -\min[-A_h(\varphi) - A_v(\theta), A_m] \quad (9)$$

$$A_m = 25 \text{ dB}$$

where, A_m is considered as maximum horizontal attenuation, φ and θ are the azimuthal and elevation angle respectively. So, the total antenna attenuation $\{A(\varphi, \theta, \theta_{tilt})\}$ at any point in space can be expressed as in Equation (9). Where, if $\theta_{tilt} > 0^o$, the antenna (of the servicing BS) is downtilted i.e. towards the earth surface and if $\theta_{tilt} < 0^o$, the antenna (of the servicing BS) is uptilted i.e. away from the earth surface (towards the horizon).

The elevation and azimuth patterns of a V65S-1XR configured tri-sector antenna at 1900 MHz and 2600 MHz frequencies are shown in Figure. 3[28].



(a) **(b)**

Figure 3: (a)Elevation Radiation Pattern and (b) Azimuth Radiation Pattern

The 1-D antenna gain in random direction can be modeled as [29],

$$G(\varphi, \theta) = \max[G(\varphi) + G(\theta), SLL_0] + G_0 \tag{10}$$

For the peak antenna gain G_0(dBi), corresponding azimuthal antenna gain $G(\varphi)$ and elevation antenna gain $G(\theta)$ with an overall sidelobefloor SLL_0 (dB).

As stated in [27], the 3-D antenna gain can be expressed as,

$$G(\varphi, \theta, \theta_{tilt})|_{dBi} = G_h(\varphi)|_{dBi} + G_v(\theta, \theta_{tilt})|_{dBi} + G_{T,max}\big|_{dBi} \tag{11}$$

where, $G_{T,max}\big|_{dBi}$ is considered as the maximum antenna gain.The Equation (11) can be approximated as,

$$G(\varphi, \theta, \theta_{tilt})|_{dBi} = A(\varphi, \theta, \theta_{tilt}) + G_{T,max}\big|_{dBi} \tag{12}$$

3.2Application of RL Algorithm

To optimize the coverage dynamically and adaptively, it is necessary to operate the BS antenna angle tilt in a self-organized manner. RL-based solution is integrated to facilitate this behavior of the antenna. Another parameter is known as the weighting factor ($Ш_n, 0 < Ш_n < 1$) which determines the priority of the user hotspot for receiving a high data rate. The application of the RL based algorithm to find the optimum antenna angel tilt for maximum user cluster can be clearly perceived by following the steps as specified below;

Algorithm

Step1: Inspect all the possible angles of the antenna {States 'S', here, maximum possible states are 5 (i.e.$0°, 2°, 4°, 6°, 8°, 10°$)}.$\theta_{min} \leq \theta_{opt} \leq \theta_{max}$. Where, $\theta_{min}, \theta_{max} \& \theta_{opt}$ are the minimum, maximum and optimum BS antenna tilts respectively.

Step 2: Calculate all the user densities (Let, $U_1, U_2, \dots \dots . U_N$) (In this work 5 user densities are considered).

Step 3: Calculate,

$$\text{maximum user density} = \max\left(U_1, U_2, \dots \dots . U_N\right)$$

Step 4: Calculate the distance of different user densities from the serving BS (based on RSS).

Step 5: Calculate the distance of the maximum user density from the serving BS (based on RSS).

Step 6: Set the maximum coverage distance (cell) based on RSS and SINR value of the user placed at the cell edge by using step -1(Let, say it as D).

Step 7: Find the coverage distance for each tilt angle or state.

$$\left\{\text{Coverage Distance } (D_C) = \frac{D}{S}\right\}.$$

Step 8: For the present network scenario, find the optimal BS antenna tilt angle.

Step 9: By making the effective use of the obtained optimized antenna tilt angle for current network scenario, evaluate and accommodate the changes depending upon the network condition.

Step 10: Repeat the process from Step 1 to Step 9to obtain the optimum value of the tilt angel for every change in the network environment.

4. Simulation Results & Analysis

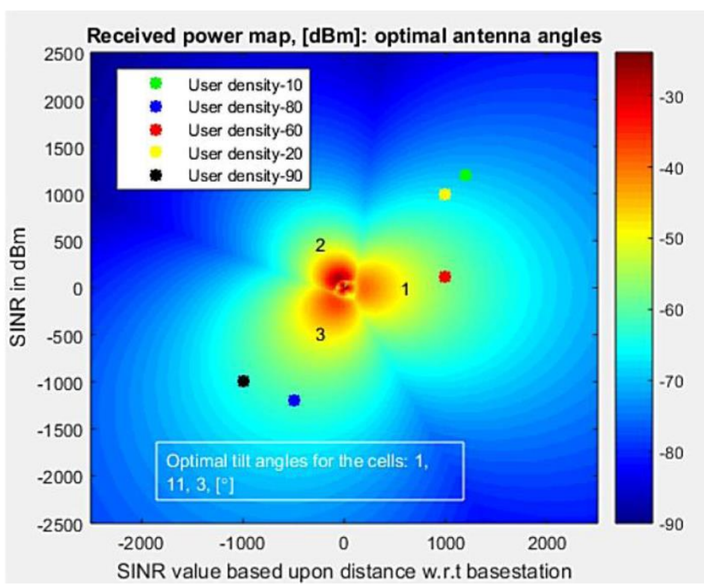
In this section, the simulation results of the proposed system model are presented. The simulation parameters used in the tests are provided with its specifications in Table 1.

Table1: Simulation Parameter

Parameters	**Specifications**
Field Dimensions	5000mX 5000m
Frequency bandwidth [27]	$\Delta f = 10MHz$
Number of user densities	5
Path-loss exponent [7]	$\alpha = 4.5$
Carrier frequency	f_c=1GHz
Number of subcarriers	$N_{SC} = 5000$
Frequency reuse factor	1
Number of cells	B = 3
Antenna Parameters	**Specifications**
Maximum horizontal attenuation	$A_m = 25$ dB

Horizontal half-power beam width [27]	$\varphi_{3dB} = 70°$
Vertical half-power beam width [27]	$\theta_{3dB} = 10°$
Vertical side lobe attenuation	$SLA_v = 20$ dBi
Minimum electrical tilt angle	$\theta_{min} = 0°$
Maximum electrical tilt angle	$\theta_{max} = 10°$
Change in electrical tilt angle in each step	$\Delta\theta = 2°$
Maximum gain of the transmitting antenna	$G_{T,max} = 14$ dBi
Transmitting power [27]	$P_T = 40$ W (46 dBm)
BS antenna height	$H_b = 32$ m
UE antenna height [27]	$H_u = 1.5$ m

The simulation is carried out by considering five different user densities (as represented in form of '*', the number of users in the densities are taken randomly), which are distributed arbitrarily in a three sectored cellular network. Here, the propagation path is considered as the simplified path-loss model. İnitially, the main lobe of the antenna pattern is set at an angle of 0° towards x-axis and then an increment of 2° (for each state) will be obtained in an anti-clockwise direction. After exploring all the possible states by using the proposed algorithm, the obtained received power map from the serving BS and the optimal tilt angel for maximum user satisfaction is shown in Figure 4.



(a)

```
DebugValue1
The optimal state for cell 3 is: 2.
The optimal downtilt angle for cell 3 is: 3 Â°
The number of satisfied user densities in the network are 5.
This is 100%!
```

(b)

```
Cell 2 is not serving any users.
Therefore, to avoid interference, the optimal downtilt angle for cell 2 is: 11 Â°
```

(c)

Figure 4: (a) Optimized received power-map; (b& c) Debug Value

From the optimized received power map as shown in Figure 4 (a), it can be observed that as cell 2 is not serving any user hotspot, so to avoid interference to other cells the optimal angle of the antenna is down-tilted. Furthermore, in this scenario,the P_T for that cell can be reduced or put off for making the network more energy-efficient (EE). Again, sector 3 is serving three different user densities (10, 20, and 60), out of which only one user density (60) is present nearby the BS. So to provide maximum numbers of user satisfaction the optimal angle for sector 3 is down-tilted ignoring the two other small number of user hotspots i.e. 10 and 20 which are present at a long distance from the BS. This also makes the network more EE, because the lesser user densities are far away from the serving BS and require maximum P_T (by making the angle up-tilt) to achieve the desired SINR level or good QoS. Sector 3 serving two user densities (80, 90), out of which the maximum user density i.e. 90 is present at a longer distance compared to the other user density. So to satisfy all the users in maximum user hotspot the optimized angle is up-tilted. From Figure 4 (b) (the captured debug value); it signifies that all the user hotspots (i.e. 100%) in simulated network are getting sufficient SINR levels. Figure 4 (c)(the captured debug value) clarifies that, as the sector 2 is not serving any user, so to avoid unnecessary interference by BS transmitting power the antenna is downtilted.

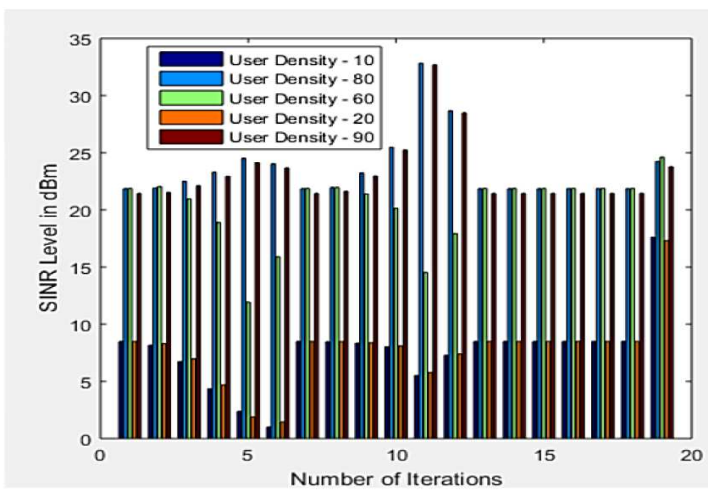


Figure 5: The SINR level of individual user densities after each iteration

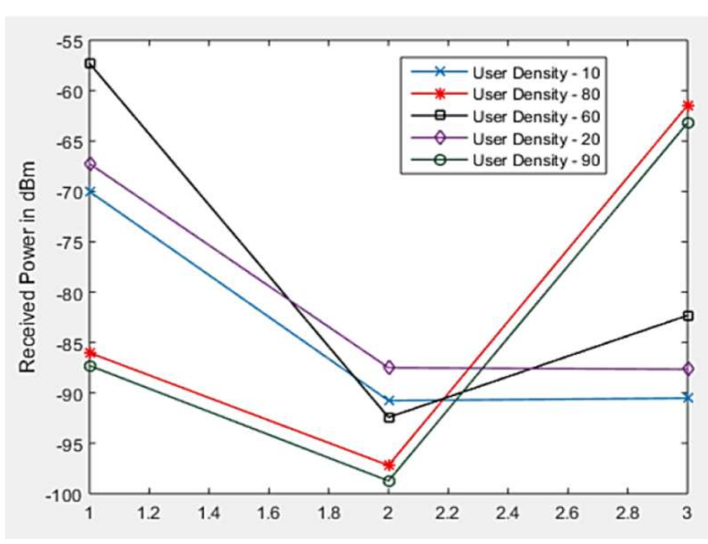


Figure 6: Received signal power by each user densities

Figure 5 shows the SINR level of each user densities w.r.t. the number iterations, where it can be observed that the SINR level varies after each iteration due to random variation in propagation channel properties. The SINR level is a function of the distance of the user clusters from their serving BS. From this figure, it can be clearly seen that due to the optimized tilt angle, the achieved SINR value for the user cluster 80 and user cluster 90 is maximum in every iteration. Figure 6 shows the RSS by each user densities, which signifies that the user densities (i.e. 80, 90) receive maximum signal strength. In fact, the RSS is a dependent parameter of the distance. From Figure 5 and 6, it can culminate that due to the remarkable improvement in the SINR value and RSS for the user clusters with the highest density the good QoS and high data rate can also be attained.

5. Conclusion

In this work, a user density-based BS antenna tilt approach for the coverage and capacity optimization for ultra-dense cellular networks is presented. The proposed method utilizes an existing RL based algorithm for its analysis. This work mainly focuses on the maximum number of user satisfaction. From the simulation results, it can be observed that due to this proposed method the coverage area of the cellular network can be optimized in such a way that a group of users with maximum density will get a high SINR value and better RSS ($\approx 100\%$ user satisfaciton). This proposed solution also improves the EE of the network by reducing or making the transmitting power off for the cell which doesn't serve any user/user density. This facilitates green communication by reducing the CO_2 emission. For future work, this work can be jointly implemented with dynamic adjustment of the BS antenna height to find better CCO in a 5G cellular network.

Declarations

Funding:Not applicable

Conflicts of interest/Competing interests: Not applicable

Availability of data and material:Not applicable

Code availability:Not applicable

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