Spectral Efficiency Self-Optimization through Dynamic User Clustering and Beam Steering

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***Abstract*—This paper presents a novel scheme for spectral efficiency (SE) optimization through clustering of users. By clustering users with respect to their geographical concentration we propose a solution for dynamic steering of antenna beam, i.e., antenna azimuth and tilt optimization with respect to the most focal point in a cell that would maximize overall SE in the system. The proposed framework thus introduces the notion of elastic cells that can be potential component of 5G networks. The proposed scheme decomposes large-scale system-wide optimization problem into small-scale local sub-problems and thus provides a low complexity solution for dynamic system wide optimization. Every sub-problem involves clustering of users to determine focal point of the cell for given user distribution in time and space, and determining new values of azimuth and tilt that would optimize the overall system SE performance. To this end, we propose three user clustering algorithms to transform a given user distribution into the focal points that can be used in optimization; the first is based on received signal to interference ratio (SIR) at the user; the second is based on received signal level (RSL) at the user; the third and final one is based on relative distances of users from the base stations. We also formulate and solve an optimization problem to determine optimal radii of clusters. The performances of proposed algorithms are evaluated through system level simulations. Performance comparison against benchmark where no elastic cell deployed, shows that a gain in spectral efficiency of up to 25% is possible depending upon user distribution in a cell.**

Keywords—User Clustering; Dynamic beamforming; Antenna tilt; azimuth; spectral sfficiency; LTE-A; Cellular networks

I. INTRODUCTION

The tremendous increase in the number of mobile devices part of connectivity of anything to anything (also called Internet of Things (IoT)) and frequent emergence of diverse technologies are exerting extra pressure for dynamic data rate demand on wireless networks. Spectrum, which is regarded as one of the scarcest resources, must be efficiently utilized to meet those demands alongside the innovation and invention of new technologies and architectures. On one hand, there are a number of schemes being researched including, among others, Massive- Multiple Input Multiple Output (MIMO), Base Station (BS) densification, mmWave networks, and decoupled control and data plane architectures, that target the 5G and beyond networks to improve overall network efficiency. This paper, on the other hand, proposes to improve network spectral efficiency by optimizing the existing network parameters such as antenna azimuth and tilt angles, within the available resources. However, the diversity of users and their spatio-temporally varying requirements mandate the future networks to be not only heterogeneous and dense but also highly elastic. High network node density further increases the complexity to manage them. Hence, manual optimization of the network becomes highly challenging [1]. Self-Organizing Networks (SON) has emerged as a technique to replace the manual handling by embedding intelligence and elasticity into the network [4]. SON enables the network to adapt to the changing environment by adjusting the network parameters autonomously. SON not only makes network highly efficient but also yields significant reduction in the network operational expenses (OPEX). In this article, we propose to optimize spectral efficiency (SE) by adaptively and simultaneously adjusting both antenna azimuth and tilt (i.e., in self-organizing manner) to steer the beam with respect to ever-changing user density and environment. To determine the highly dense regions of users within a cell, we propose and investigate three clustering algorithms, which when implemented, determine focal points in each cell. Once the clusters and their focal points are found, SE optimization algorithm is utilized to calculate new optimal azimuth and tilt values. Such online dynamic beam steering in real network could potentially be exploited using e.g., multi element antenna systems such as MIMO or massive MIMO which are being considered for emerging networks. The kind of beam steering proposed in this paper is much simpler and easier to implement as it does not require 1) tracking of individual users, 2) estimation of angle of arrival 3) estimation of channel. Instead the proposed solution requires simple antenna adjustments to change its azimuth and/or tilt by a few degrees as we will explain later.

The rest of the paper is organized as follows. Section II provides review of related work and outlines the novelty and contributions of this work. Section III presents system model while the self-optimization framework has been discussed in Section IV. Section V evaluates the performance using the numerical and simulation results. Section VI presents key conclusions.

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II. Related Work

There are various techniques proposed in literature to enhance spectral efficiency by optimizing antenna parameters. In [5], user's average throughput has been maximized using BS-coordinated tilting. Authors in [6] propose to adaptively adjust antenna tilt and pilot power to meet varying traffic load in the system. However, they take into consideration only the tilt and do not consider azimuth optimization. A similar solution is also proposed in [7] to study capacity and coverage optimization (CCO) use case of SON. However solution proposed in [7] optimizes the throughput of a single hotspot, it neither considers system-wide optimization nor does it address the dynamically changing user density throughout the cell. In [8]-[11], switched beam tilting has been proposed, in which each BS utilizes one of the many pre-determined fixed tilts to maximize the users' throughput in certain region within a cell. In [11], a framework has been proposed for dividing the cell into concentric region and applying switched beam tilting. However, solution in [11] is studied in context of an isolated cell, and does not take into account interference from neighboring cells. In our recent work [3], we proposed SON enabled system-wide SE optimization solutions for network with hotspots and relay stations. However, work in [3] only considers tilt angle as the optimization parameter. Whereas in this article we propose self-optimization of both azimuth and tilt angle for changing user density. Second distinction of this work from [3] is that, we present and compare three different user clustering algorithms to determine best representative point in a cell that can be used in the joint azimuth and tilt optimization processes. Furthermore, in this work we also present a method to determine optimal radius to cluster the users into groups. These contributions allow the optimization framework to be more user centric than that presented in [3].

The significance of this work lies in the fact that joint optimization of both azimuth and tilt affectively paves the way for newly conceived cell-less deployment architecture—an architecture where cells won't have rigid foot prints. In such architecture active cells' shapes, sizes and numbers will vary with user distribution and demand [1]. Such elastic cell-less architecture is one of the key features being envisioned for 5G. Proposed framework can be implemented in such elastic cell-less architecture by harnessing the beam steering capabilities of multi antenna element systems which are also a key component of 5G landscape.

The contribution of this paper is three fold. First, we propose a framework to optimize SE by adjusting antenna azimuth and tilt in self-organizing manner. Second, we propose and compare three algorithms to find focal points in each cell which can best represent given user distribution in the optimization process. This representation is manifested to reduce the computational complexity of the solution. In addition to that, we also formulate an optimization problem to determine the optimal radii within which the user density is the highest. These focal points and optimal radii provide us more accurate information about the location of the highest user density in the cell. We compare the results with the conventional fixed azimuth and tilt angle orientation. Results show that up to 25 % gain in spectral efficiency can be achieved by using the proposed framework.

III. System Model

We consider a downlink transmission in multicellular network in which each BS has three sectors to begin with (which will be called hereafter 'cell'), each covering a span of 120 degree, as shown in Fig.1. It is assumed that all user equipment (UEs) are outfitted with omnidirectional antenna with 0 dB gain. We use spectral efficiency (SE) in b/s/Hz as the optimization metric and we define it as the long term average bandwidth normalized throughput on a link given by $\log_2(1 + SIR)$, where SIR stands for Signal to Interference Ratio.

Let N denote the set of points corresponding to transmission antenna location of all sectors and K denote the set of points representing the location of user in the system. The geometrical SIR perceived at a user location k being served by n^{th} sector can be given as:

$$\eta_k^n = \frac{P^n G_k^n \alpha (d_k^n)^{-\beta}\, \sigma_k^n}{\sum_{\forall m \in N \setminus n} (P^m G_k^m \alpha (d_k^m)^{-\beta}\, \sigma)};\, m,\, n\, \in N,\, k \in K \quad (1)$$

where P^n indicates transmission power of the n^{th}cell, d_k^n is the distance between transmitting antenna location n and UE location k. α and β are pathloss model coefficient and exponents, respectively. σ_k^n represents shadowing experienced

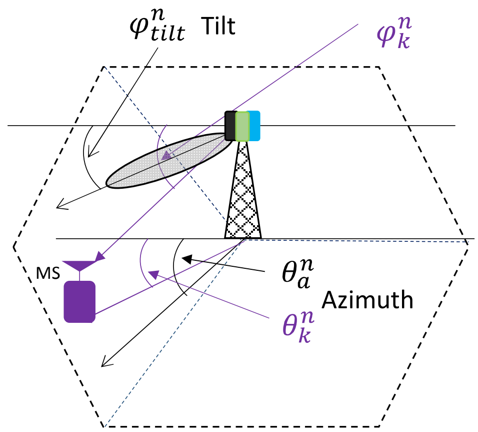

Figure 1. Illustration of antenna tilt and azimuth angle

by users at location k while receiving signal from n^{th} transmitting antenna. G_k^n represents antenna gain perceived at k user location from n^{th}antenna. As proposed by 3GPP [13], the three dimensional antenna pattern can be given as

$$G_k^n = 10^{0.1\left(\begin{array}{c}\lambda_v\left(G_{max} - \min\left(12\left(\frac{\varphi_k^n - \varphi_{tilt}^n}{B_v}\right)^2, A_{max}\right)\right) + \\ \lambda_h\left(G_{max} - \min\left(12\left(\frac{\theta_k^n - \theta_a^n}{B_h}\right)^2, A_{max}\right)\right)\end{array}\right)} \quad (2)$$

and with simplification introduced in [13], the above expression is reduced to

$$G_k^n = 10^{-1.2\left(\lambda_v\left(\frac{\varphi_k^n - \varphi_{tilt}^n}{B_v}\right)^2 + \lambda_h\left(\frac{\theta_k^n - \theta_a^n}{B_h}\right)^2\right)} \quad (3)$$

where φ_k^n is the vertical angle at the n^{th} BS in degrees from reference axis to the k^{th} UE. φ_{tilt}^n is the tilt angle of the n^{th} cell as shown in Fig.1. Also, θ_a^n represents azimuth angle orientation with respect to horizontal reference axis and θ_k^n is the angular distance of the k^{th} user from horizontal reference axis. For simplicity, we use substitution in (1) as follows:

$$\delta_k^n = \sigma_k^n \alpha (d_k^n)^{-\beta}\ ,\ \delta_k^m = \sigma_k^m \alpha (d_k^m)^{-\beta} \text{ and } \mu = \frac{-1.2\lambda_v}{{B_v}^2}$$

Using the above substitution and the gain from (3) into (1), we get the SIR at the UE represented as

$$\eta_k^n = \frac{\delta_k^n 10^{-1.2\left(\lambda_v\left(\frac{\varphi_k^n-\varphi_{tilt}^n}{B_v}\right)^2+\lambda_h\left(\frac{\theta_k^n-\theta_a^n}{B_h}\right)^{2}\right)}}{\sum_{\forall m\in N\setminus n}\left(\delta_k^m 10^{-1.2\left(\lambda_v\left(\frac{\varphi_k^m-\varphi_{tilt}^m}{B_v}\right)^2+\lambda_h\left(\frac{\theta_k^m-\theta_a^m}{B_h}\right)^2\right)}\right)} \quad (4)$$

where, $n, m \in N$; the indexes n, m and N represents the serving BS, interfering BS and the set of all the BSs respectively.

IV. Self Organizing Framework

In this section we detail the framework that decomposes the large scale problem into small scale problems to achieve distributed self-organizing solution. However, since the framework is built upon our recent work in [3], we will describe it briefly. We then propose clustering algorithms to determine cell focal points. At the end of this section, we formulate problem to determine the optimal radius of clusters within the network cells.

A. Problem Formulation

As assumed, set K represents the location of all the users in the system. So, the bandwidth normalized system throughput optimization can be expressed as (5) below.

$$\max_{\varphi_{tilt}^N,\theta_a^N} \hat{\xi} = \max_{\varphi_{tilt}^N,\theta_a^N} \sum_{\forall k\in K} log_2\left(1+\eta_k^n\left((\varphi_{tilt}^N,\theta_a^N)\right)\right) \quad (5)$$

It can be easily noticed that η_k^n is a function of system wide azimuth and tilt angle. Since K represents user and is usually a large number, which indicates that (5) is a large scale non-linear problem.

To overcome the difficulty of solving a large scale optimization problem, that will require real-time locations of all users in the system, we exploit the concept of determining a single focal point in each cell. The key attribute of such point is that it can affectively represent all the users in that cell during the optimization process. The validity of this approach was demonstrated in Lemma 1 in [3] in context of tilt optimization. In this paper we extend that approach for joint azimuth and tilt approach and propose, in next section, three alternative algorithm to heuristically compute such single point for each cell.

Let S denotes the set of all such focal points in all the cells. Then the objective function in (5) can be optimized only with respect to those focal points and thus can be approximated as

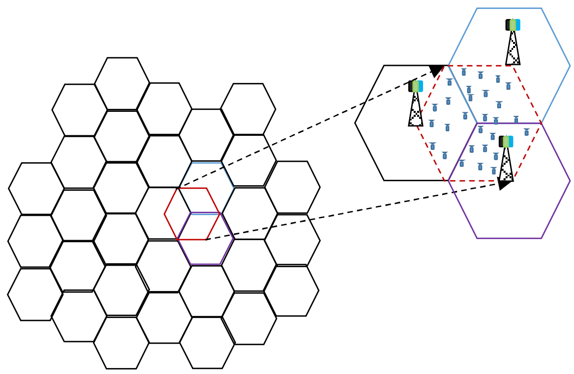

Figure 2. Illustration of decomposition into triplets

$$\max_{\varphi_{tilt}^N,\theta_a^N} \sum_{\forall s\in S} log_2\left(1+\eta_s^n\left((\varphi_{tilt}^N,\theta_a^N)\right)\right) \quad (6)$$

Thus, compared to problem (5) which optimizes the antenna azimuth and tilt with respect to every user 'K' reduces to optimization problem (6) which optimizes with respect to only few focal points 'S' in the system, reducing the computational complexity.

- *Achieving a distributed solution*

Equation (6), though has far less number of variables than (5), its solution still requires global coordination among all cells. A distributed solution can be enabled by exploiting the fact that in low power, small cell, high frequency band deployments being envisioned for 5G, interference will not propagate far beyond immediate neighbors. Thus the problem in (6) can be further approximated as

$$\max_{\varphi_{tilt}^N,\theta_a^N} \hat{\xi} = \max_{\varphi_{tilt}^N,\theta_a^N} \sum_{\forall s\in S} log_2 \frac{1}{|N|}\left(1+\hat{\eta}_s^n\left((\varphi_{tilt}^N,\theta_a^N)\right)\right) \quad (7)$$

where $\hat{\eta}_s^n$ represents the approximate SIR at the optimal point that considers observations from only its two immediate neighbors as shown in Fig. 2. Lemma 1, corollary 3 in [3], actually proves that for large β, $\hat{\xi}$ approaches the true value ξ. One particular scenario where beta is expected to be significantly large is mmWave based deployment [12], which is being considered as an integral part of 5G landscape. Thus, according to the propositions 1 and 2 in [3], (7) can be expressed as

$$\hat{\xi}_{N,max} = \frac{1}{|N|}\sum_{\forall n\in N}\left\{\max_{\varphi_{tilt}^N,\theta_a^N} \frac{1}{|T_n|}\sum_{\forall s\in S_n} log_2\left(1+\hat{\eta}_s^n\left((\varphi_{tilt}^N,\theta_a^N)\right)\right)\right\} \quad (8)$$

where, S_n is the set of focal points in n^{th} triplet and $|S_n| = |T_n| = T_n = 3, \forall n = N$.

Thus large scale centralized given in (6) is now reduced to small scale distributed optimization given in (8), for each triplet to be solved independently.

B. Throughput Optimization of Cluster in Each Cell

From the analysis presented above our problem in (5) has now been reduced to optimization of azimuth and tilt angle with respect to single focal points (to be determined) in individual triplets of cells. This optimization problem to be solved for every triplet is given as

$$\max \hat{\xi}\ (\varphi_{tilt}^1, \phi_a^1, \varphi_{tilt}^2, \theta_a^2, \varphi_{tilt}^3, \theta_a^3) \tag{9}$$

$$\text{s.t.} \qquad 0 < \varphi_{tilt}^1, \varphi_{tilt}^2, \varphi_{tilt}^3 < 90 \tag{10}$$

$$0 < \theta_a^1 < 120 \tag{11}$$

$$121 < \theta_a^2 < 240 \tag{12}$$

$$241 < \theta_a^3 < 360 \tag{13}$$

Equation (14) presents the full form of objective function expressed in (9). Although the tilt angle varies from 0 to 90, in practice, the optimal value of tilt generally varies from 0 to 20 degree unless all users in the cell are concentrated at the base of base station. On the other hand in tri-sector system the optimal value of azimuth can be safely assumed to lie within ± 15 degree of the nominal azimuth value unless user distribution is extremely skewed towards one edge of the sector, in which case it will be better to serve those users with that sector toward which user distribution is skewed. Our repeated computer simulations show that capping the range of azimuth adaptation is also necessary to limit inter-sector interference. These observations shortens the search space to $20 \times 20 \times 20 \times 15 \times 15 \times 15 = 27 \times 10^6$. This search space can be explored by any state of the art heuristic search algorithm that promises a global solution despite of non-convexity of the objective function. Noting that solution space, in this paper, is fairly small and well defined, we apply Simulated Annealing (SA) to explore the optimal azimuth and tilt and to make sure a global optimal within the curtailed search space is guaranteed.

C. Proposed Algorithms for Determining Cell Locus through Clustering

We investigate three different clustering algorithms to determine focal point (highly user dense region) in each cell which then can be used for azimuth and tilt optimization in real-time fashion. The key common idea behind the three clustering algorithms is that for every user in each cell, the number of users within a pre-specified radius will be determined. The users will be grouped into a cluster if they lie within that radius and if they meet the selected key performance indicators (KPI) , including SIR, RSL and MS-BSs distance. The underlying KPI used to group users differentiates the three clustering algorithms. Users are grouped in clusters based on the selected KPI. The cluster which has the highest number of users is then chosen as the desired cluster. The mean (focal) point of the chosen cluster, for each cell in a triplet, is then determined. Those focal points are then used as the representative point with respect to which the optimization of antenna azimuth and tilt is performed in each triplet. In this study we assume cluster radius of 150 meter, but optimal radii of clusters will vary with cell radii, user distribution and propagation conditions.

The clustering algorithms based on different KPIs are described as follows:

a) Clustering based on SIR: Since users in each cell are served by their serving BS, other BSs in the triplet work as interferer. *In this case,* we first find the mean SIR of every cell, which acts as threshold SIR (SIR_{th}) for the users to be grouped into a cluster in addition to the condition that they should lie within the radius. In other words, to form the cluster around every user, the cluster user*s* should be within the radius and the*ir* received SIR should be greater than or equal to SIR_{th} of that cell under evaluation. Similar procedure is followed in others cells in the triplet, which will have their own $SIR_{th.}$ The pseudocode for the algorithm is given in Fig. 3. Note that in emerging and futre cellular networks, with advent

$$\hat{\xi} = log_2\left(1+\frac{\delta_1^1 10^{-1.2\left(\lambda_v\left(\frac{\varphi_1^1-\varphi_{tilt}^1}{B_v}\right)^2+\lambda_h\left(\frac{\theta_1^1-\theta_a^1}{B_h}\right)^2\right)}}{\left(\delta_1^2 10^{-1.2\left(\lambda_v\left(\frac{\varphi_1^2-\varphi_{tilt}^2}{B_v}\right)^2+\lambda_h\left(\frac{\theta_1^2-\theta_a^2}{B_h}\right)^2\right)}\right)+\left(\delta_1^3 10^{-1.2\left(\lambda_v\left(\frac{\varphi_1^3-\varphi_{tilt}^3}{B_v}\right)^2+\lambda_h\left(\frac{\theta_1^3-\theta_a^3}{B_h}\right)^2\right)}\right)}\right)$$
$$+\ log_2\left(1+\frac{\delta_2^2 10^{-1.2\left(\lambda_v\left(\frac{\varphi_2^2-\varphi_{tilt}^2}{B_v}\right)^2+\lambda_h\left(\frac{\theta_2^2-\theta_a^2}{B_h}\right)^2\right)}}{\left(\delta_2^1 10^{-1.2\left(\lambda_v\left(\frac{\varphi_2^1-\varphi_{tilt}^1}{B_v}\right)^2+\lambda_h\left(\frac{\theta_2^1-\theta_a^1}{B_h}\right)^2\right)}\right)+\left(\delta_2^3 10^{-1.2\left(\lambda_v\left(\frac{\varphi_2^3-\varphi_{tilt}^3}{B_v}\right)^2+\lambda_h\left(\frac{\theta_2^3-\theta_a^3}{B_h}\right)^2\right)}\right)}\right)+\ log_2$$
$$\left(1+\frac{\delta_3^3 10^{-1.2\left(\lambda_v\left(\frac{\varphi_3^3-\varphi_{tilt}^3}{B_v}\right)^2+\lambda_h\left(\frac{\theta_3^3-\theta_a^3}{B_h}\right)^2\right)}}{\left(\delta_3^1 10^{-1.2\left(\lambda_v\left(\frac{\varphi_3^1-\varphi_{tilt}^1}{B_v}\right)^2+\lambda_h\left(\frac{\theta_3^1-\theta_a^1}{B_h}\right)^2\right)}\right)+\left(\delta_3^2 10^{-1.2\left(\lambda_v\left(\frac{\varphi_3^2-\varphi_{tilt}^2}{B_v}\right)^2+\lambda_h\left(\frac{\theta_3^2-\theta_a^2}{B_h}\right)^2\right)}\right)}\right) \tag{14}$$

```
Algorithm 1: SIR based Clustering
Number of user in the cell: N, Radius of Cluster: R, User count: C_i
for each cell do
   calculate mean SIR of the cell: SIR^th
    for each user do
         calculate distance from other users d_ij , i≠j; i, j = 1,…N
         if d_ij <R and SIR_i ≥ SIR^th , then
            C_i= C_i +1 ;
         else
           continue;
         end
    end
    select cluster with maximum user: argmax(C_i,…, C_N)
end
```

Figure 3. Pseudo-code for SIR based clustering

of location based services, accurate locations of indiviual users within a cell is known by the network. Given that location information is available at each base station, the SIR can be esitmated using (4). Alternatively, third generation partnership project (3GPP) Channel Quality inidicator (CQI) reported by users can also be exploited to estimate real time SIR. Thus, the clustering alrogirthms proposed in this paper are implementable in an online fashion with no additional signalling overhead.

b) Clustering based on RSL: This method is similar to the one with SIR with the difference that SIR is replaced with RSL. The pseudocode for this algorithm is given in Fig. 4 below. In emerging cellular neworks, , minmization of drive test (MDT), recently standardized by third 3GPP, contains RSL reports [16]. Thus standardization of MDT allows online implementaiton of the algorithm in Fig. 4 without additional signalling overhead.

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Algorithm 2: RSL Based Clustering
Number of user in the cell: N; Radius of Cluster: R, , User count: C_i
for each cell do
    for each user do
         calculate distance from other users d_ij , i≠j; i, j = 1,…N
         calculate RSL from BSs: RSL_serv, RSL_int
         if d_ij <R and RSL_serv < RSL_int , then
            C_i= C_i +1 ;
         else
           continue;
         end
    end
    select cluster with maximum user: argmax(C_i,…, C_N)
end
```

Figure 4. Pseudo-code for RSL based clustering

c) Clustering based on distance from the BS: This method also considers the highest number of user within the prespecified cluster radius with a center being the base station. However, the second criteria in this scheme is that the distance of the user from its serving BS is assumed to be lesser than the distance to the interfering BSs. The cluster formed using this method will ensure that it is nearer to the serving BS. This algorithm will be more useful to realize under cell-less architecture where any user can connect to any BS depending upon signal availability. The pseudocode for this algorithm is given in Fig. 5.

```
Algorithm 3: Distance Based Clustering
Number of user in the cell: N, Radius of Cluster: R, User count: C_i
for each cell do
    for each user do
         calculate distance from other users d_ij , i≠j; i, j = 1,…N
         calculate distance from BSs: d_serv, d_int
         if d_ij <R and d_serv < d_int , then
            C_i= C_i +1 ;
         else
            continue;
         end
    end
    select cluster with maximum user: argmax(C_i,…, C_N)
end
```

Figure 5. Pseudo-code for distance based clustering

The choice of algorithm depends upon the motive behind clustering. For example, SIR based clustering will ensure that most of the users will be served with higher throughput most of the time. Similarly RSL based clustering can be chosen where throughput fairness is the major objective. While distance based clustering can be used for scenarios where there are no high rise buldings and towers that can work as interferers. Since their implementaiton, performance and complexity vary, there lies trade-off to be considered while selecting one scheme over the other. We also noticed that all three algorithms require the user density to be the highest but the location of the cluster will differ based on the selected KPI. .

D. Problem Formulation for Optimal Radius

As discussed earlier the optimal threshold radii used in clustering algorithms will vary with a number of factors: cell size, user distribution, etc. Hence it is essential to determine the optimal radius. Furthermore, optimal radius calculation becomes more important while realizing cell-less architecture. In such cases, optimal radius would play key role in determining width of the beam directed toward each user..

While maximize spectral efficiency, we consider clustering based on SIR and the highest user density. Thus the spectral efficiency is a function of SIR at the user and total number of user (denoted by *N*) in the cell.

$$SE\ (\xi) = f(SIR\ (azimuth, tilt), N) \tag{15}$$

Although the radius may vary, we assume that optimal radius is employed and user distribution is assumed to have values of $50 < r < 150$.

If the radius of the hexagon is denoted by *R*, then the optimal radius can be determined by solving

$$\hat{r} = \max_{r}\left(\left(\pi r^2 \times \frac{2N}{3\sqrt{3}R^2}\right) \times SIR_n\right) \tag{16}$$

$$\text{s.t.} \qquad 50 < r < 150 \tag{17}$$

where $\hat{r}$ denotes the optimal radius of the cluster. It is important here to note that the cluster of range of radius in (17) is formed around every user and the radius satisfying (16) is chosen to be optimal. The SIR_n indicates the SIR at each user $(n = 1,..,N)$. The above optimization problem is a differentiable and constrained problem; it can be easily solved through any nonlinear optimization algorithm.

V. PERFORMANCE EVALUATION

In this section, we present numerical results using 3GPP recommended simulation parameters for LTE systems, given in Table 1.

Table 1. Simulation Parameters

Parameters	Values
System Topology	19 BS with 3 sectors per BS
BS Transmission Power	46 dBm
BS Inter site Distance	500 meter
BS and UE height	32 meter, 1.5 meter
UE Antenna Gain	0 dB
Vertical Beamwidth	70^0
Horizontal Beamwidth	10^0
Vertical Gain Weight, λ_v	0.5
Horizontal Gain Weight, λ_h	0.5
Maximum Gain, G_{max}	18 dB
Maximum Attenuation, A_{max}	25 dB
Shadowing	8 dB
Frequency	2 GHz
Path Loss Model	3GPP Urban Macro

To obtain the optimum azimuth and tilt, we applied heuristic search method 'Simulated Annealing' [15]. The detail of which is skipped because of limited space. We also implemented the optimization technique of sequential quadratic programming (SQP). Optimal azimuth and tilt were found using a brute force algorithm (SA) and the obtained results compared to those achieved using the SQP algorithm. The SQP results were confirmed and validated. We compared the bandwidth normalized throughput obtained by the proposed self-organized azimuth and tilt optimization framework, referred to as SATO hereforth, with those obtained using fixed azimuth and tilt which is referred to as centralized azimuth and tilt optimization (CATO) in [3].

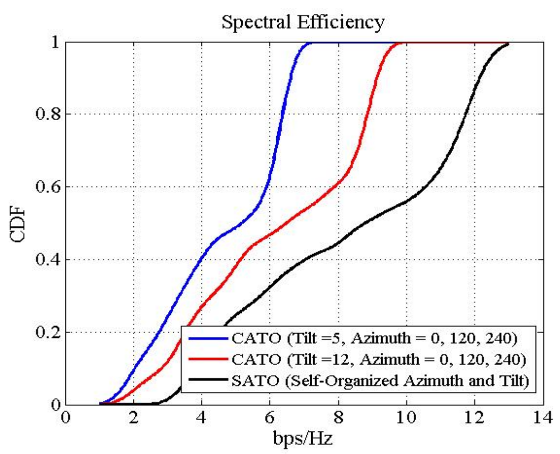

Figure 6. CDF representation of SE achievable using CATO and SATO frameworks

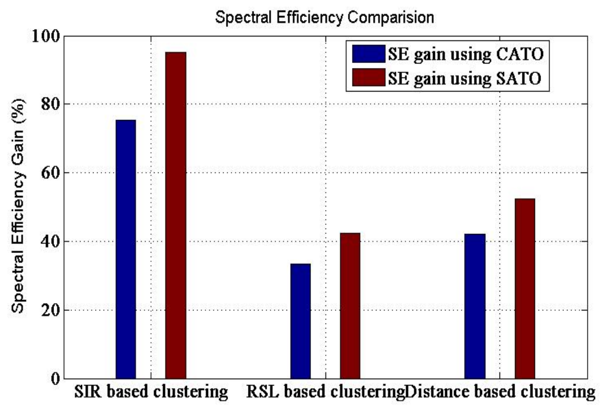

Figure 7. Comparison of Bandwidth normalized throughput obtained using CATO and SATO

In Fig. 6, we plot the SE commutative density function (CDF) achieved at the focal points using the proposed SATO framework. Then we compare the CDF against that obtained using CATO. We used fixed tilt of 5^o and 12^o and fixed typical azimuth of 0^o, 120^o, 240^o for cell 1, 2 and 3, respectively. We observe that at lower tilt of 5^o, the performance is poor, because at smaller tilt, the beam is pointing towards the edge of the cell and hence exposed to higher interferences from other BSs. At the fixed tilt of 12^o, and fixed regular azimuth, the performance improves as the interference from other BSs decreases. However, if the tilt goes on increasing the performance will degrade and limit the coverage at the cell edge. For uniform user distribution and for standard BS height and user end (UE) height, the fixed optimal tilt is centered around 12^o[3]. We observe that using the SATO framework, SE gain of 1 to 3 bps/Hz is achievable over using the CATO framework. The SATO framework adjusts its azimuth and tilt automatically based on user density, thus optimizing the throughput at UE. It is clearly confirmed that the SATO technique outperforms the fixed scheme CATO.

Figure 7 presents the effect of different clustering techniques on SE performance, as the location of optimal focal points will vary for the investigated clustering schemes. It can be noticed that it is possible to achieve 10% to 25% gain in spectral efficiency, the highest being for the clustering based on SIR. This is intuitive because SIR based clustering considers not only the signal strength of the serving BS but also the interferences from other BSs. Other clustering algorithms although considers signal strength as well as the relative distance to the BS, they don't incorporate interference directly. Hence their performances are not as good as that of SIR based SATO. However, it's worth noting that the RSL and distance-

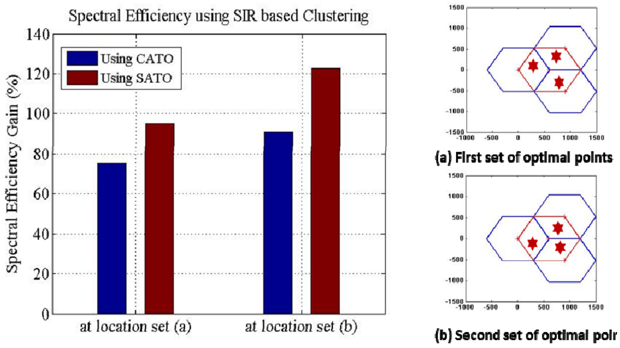

Figure 8. SE gain using CATO and SATO for different focal points based on SIR clustering

-based SATO are implementable with lower computational complexity thereby offering a trade-off between performance and complexity.

Moreover, for each algorithm the gain in SE varies depending upon the location of the focal points determined through clustering process. Figure 8 shows the variation in SE gain due to different focal point locations determined using SIR based clustering.

VI. CONCLUSION

In this paper, we presented two important concepts implemented toward optimization of a system-wide SE. First, we discussed and analytically developed the framework to simultaneously configure two key antenna parameters (azimuth and tilt) in self-organizing manner. We decomposed the large-scale computationally taxing task into small-scale tasks by introducing the concept of triplet. Second, we determine a single focal point in each cell of a triplet that can be used to represent all the users in each cell. We evaluated three different clustering algorithms used to calculate the focal points that can best represent a given user distributions. These algorithms offer different levels of tradeoffs in implementation complexity and performance gain. The SIR based clustering algorithm offers the highest gain. We also proposed a method to determine optimal radius of a user cluster that further enables dynamic user centric optimization, which is essential to manage the continuously changing of user spatial distribution. We compared the SE gain against the conventional setting (fixed azimuth and tilt implementation). Obtained results confirm a 10% to 25 % gain using the proposed scheme. The proposed framework is expandable towards cell-less deployment architecture in next generation network 5G, where cells are expected to adapt their sizes and shapes in user centric fashion by harnessing the flexibility inherent in multi element antenna systems. The proposed solution is also applicable to mmWave based systems as the interference in such system is mainly inter-sector interference and interference from neighboring cells can be neglected to implement distributed, low complexity, online cell footprint adaptation to make the best of spatio-temporally changing user distributions.

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