Adaptive Beamforming based Inband Fronthaul for Cost-Effective Virtual Small Cell in 5G Networks

Yanan Liu¹, Xiaoyu Duan¹, Gary Boudreau², Akram Bin Sediq², and Xianbin Wang¹

¹Western University, London, Ontario, Canada
²Ericsson Canada, Ottawa, Ontario, Canada
Email: xianbin.wang@uwo.ca

Abstract—In order to exploit the potential capacity of 5G, the deployment of ultra-dense small cells is an approach that can dramatically increase the radio resource reuse factor and network capacity. However, network densification with a large number of small cells brings challenges due to increased network complexity, deployment cost and inter-cell interference. In this paper, a new 5G architecture with virtual small cells (VSCs), which are dynamically formed by grouping a number of user devices in close proximity and adapted according to traffic condition, is proposed to improve the cost and energy efficiency compared with the traditional fixed deployment of small cells. In each virtual small cell, one mobile device is selected as a cell head (CH) to aggregate intra-cell traffic using unlicensed band transmissions and then communicates with its macro-cell base station in a licensed band through beamformed transmission, which reduces the inter-cell interference and improves spectrum efficiency. In this paper, a highly directional beamforming technique is employed to enable a dedicated inband fronthaul link for VSC. Our work focuses on how to design adaptive beamforming to minimize the transmit power under throughput requirements and power constraints. Both the mathematical analysis and simulation results demonstrate that VSCs can increase power efficiency dramatically while providing flexibility and reduced cellular load, when compared with macrocell only deployment and traditional fixed small cells scenario.

Index Terms—5G; Beamforming; Cell Formation; Massive MIMO; Virtual Small Cell

I. INTRODUCTION

With the explosive proliferation of smart devices, the dramatic increase of mobile data traffic and emerging applications particularly Internet of things (IoT), the upgrading of cellular networks and deployment of new infrastructures to support the needed data increase is inevitable in 5G networks [1]. As a result, heterogeneous networks (HetNet) with overlaid densified small cells deployed on top of cellular networks are widely considered as a promising solution for 5G. Small cells (SCs) improve the overall network capacity by installing many small base stations with reduced cell sizes and transmission distance.

However, fixed deployment of a large number of small cells in 5G HetNet is neither cost-effective nor energy efficient. To support such ultra-dense small cell networks, direct connections between SCs and macro base stations (MBS) become more complicated due to the deployment of excessive optical fronthaul and backhaul links [3]. Maintaining a large number of small cells also requires tremendous computational resources and signalling overhead, which places a heavy burden on network management [4]. Furthermore, dense SCs could introduce severe inter-cell interference due to spectrum reuse, which is the key limiting factor of cellular network capacity [5].

Therefore, grouping multiple user devices to form flexible virtual small-cells within the integral cellular network infrastructure is envisioned as a cost-effective alternative. In [6] and [7], the authors proposed to use directive beams to support dense traffic areas adaptively. However, users in each beam still communicate with MBS in the cellular band, which introduces additional co-channel interference and signalling overhead. Therefore, we propose a cellular network assisted virtual small cell (VSC) design for 5G networks in this paper to reduce co-channel interference by utilizing an unlicensed band within VSCs and beamformed trunk link transmission between MBS and VSCs. Specifically, the VSCs are formed adaptively under the coordination of cellular MBS when needed. In each VSC, appropriate mobile devices are selected as cell head (CH) candidates and serve as the CH in turn. The CH then aggregates intra-cell traffic in the unlicensed band and relays the combined traffic to an MBS in the cellular band.

Using massive MIMO techniques, large scale antenna array is adaptively employed in this paper for a highly directional beam to cover VSCs. With spatially confined transmission using cellular band radio resources, high throughput can be achieved on the trunk link between the MBS and the CH. However, the coverage and location of VSCs are not fixed due to dynamic traffic load and user’s mobility. Therefore, we focus this study on how to realize the adaptive beamforming based on the proposed VSCs system model so that the virtual small cells with changing location and radius are always effectively covered. As the battery capacity is a bottleneck of mobile devices and power efficiency is essential for MBSs, an optimal beamforming design scheme is proposed to minimize the total power consumption under constraints of maximum transmit power and required throughput rate of each user. The problem above is further divided into two sub-optimal problems to reduce the computational complexity of the proposed optimal method with comparable performance.

The remainder of this paper is organized as follows. In Section II, the system model of VSCs proposed in this paper is introduced. The beamforming design is formulated as an
optimal problem in Section III-A, and the optimal and sub-
optimal solutions are elaborated in Section III-B and III-C,
respectively. Section IV presents our main results regarding
power consumption and system performance of VSCs com-
pared with the macro-cell only scenario and traditional small
cells scenario. Finally, the conclusion is drawn in Section V.

II. SYSTEM MODEL

A. Network Architecture

In order to support high system capacity with low deploy-
ment cost and signalling overhead, VSC design is proposed in
this paper to realize cost-effective 5G networks. Regarding
the system model, we consider a heterogeneous network
architecture consisting of one macro cell and \( S \) virtual small
cells, where \( K \) users are distributed in the coverage of the
macro cell, as shown in Fig. 1. Based on the traffic load and the
location information of users, VSC can be formed adaptively
under the guidance of cellular network [8]. It is assumed that
a VSC formation server located in the cloud is in charge of all
the computation and execution of virtual small cell formation
and maintenance procedures, as shown in Fig. 1.

Noted that compared with traditional small cells, there is not
fixed access point in VSC. Within each VSC, some devices
with better channel quality as well as the power supply are
selected as CH candidates. These CH candidates serve as the
CH in turn to guarantee fairness. The CH (coloured in red) is
then responsible for aggregating the cluster traffic in the un-
licensed band and communicate with the MBS in the cellular
band [9]. The coverage of VSCs is limited by the transmission
range of unlicensed band protocol and power constraints.
Therefore, the users can be divided into two groups: one
whole of users communicate with MBS directly and denoted by
\( U = \{1, ..., L\} \), while the others are associated with CHs of
their VSCs and denoted by \( U^C \), where \( U \cup U^C = \{1, ..., K\} \).

It is assumed that each CH is equipped with \( N_{CH} \) antennas.
The macro BS is equipped with \( N_{BS} \) antennas, and the value
of \( N_{BS} \) should be large enough to realizations massive MIMO
transmission. Relying on massive MIMO technique, a highly
directional beam can be formed adaptively to cover VSCs and
work as the fronthaul link between CH and MBS.

B. Channel Model for Beamformed Fronthaul

To keep up with the changes in the coverage and location of
VSCs, the antenna radiation pattern, including the beamwidth
and steering of MBS, should be adjusted adaptively. This
adjustment of antenna radiation pattern will result in channel
variation for the beamformed fronthaul link. Therefore, the
analysis of antenna radiation pattern is necessary before the
discussion of the channel model for the beamformed fronthaul.

The VSC formation procedure defines the center and opti-
um radius of the virtual cells. The procedure details of cell
formation is given in [7] and this paper mainly focus on
adaptive beamforming design for VSC. Based on the location
information of MBS and VSCs, the vertical steering and the
beam width of the MBS beamforming can be obtained [6]

\[
\theta_{tilt} = -\tan^{-1}\left(\frac{h_{MBS}}{d}\right) \text{ (rad)},
\]

\[
\theta_{3dB} = 2\left[ -\tan^{-1}\left(\frac{h_{MBS}}{d - r}\right) - \tan^{-1}\left(\frac{h_{MBS}}{d + r}\right) \right] \text{ (rad)},
\]

where \( r \) represents the radius of VSC, \( d \) denotes the distance
from the MBS to the center of VSC and \( h_{MBS} \) is the antenna
height of MBS. Similarly, the beam width and the steering of
beamforming in horizontal plane can be obtained [6]

\[
\varphi_{tilt} = -\tan^{-1}\left(\frac{y - y'}{x - x'}\right) \text{ (rad)},
\]

\[
\varphi_{3dB} = 2\left[ \tan^{-1}\left(\frac{r}{d}\right) \right] \text{ (rad)},
\]

where \((x, y)\) and \((x', y')\) are coordinates of the center for MBS
and VSC, respectively. By using massive MIMO, 5G base
stations will be able to steer its radiation pattern with increased
spatial selectivity both horizontally and vertically [10]:

\[
A_H(\varphi) = -\min\left[ 12\left(\frac{\varphi_{tilt}}{\varphi_{3dB}}\right)^2, 30 \right] \text{ dB},
\]

\[
A_V(\theta) = -\min\left[ 12\left(\frac{\theta_{tilt} - \frac{\pi}{2}}{\theta_{3dB}}\right)^2, 30 \right] \text{ dB}.
\]

Based on above analysis, the antenna radiation pattern of
MBS is given by [10]

\[
A(\varphi, \theta) = -\min\left\{ -\left( A_H(\varphi) + A_V(\theta) \right), 30 \right\} \text{ dB}. \quad (4)
\]

The channel model \( h_l \in \mathbb{C}^{1 \times N_{BS}} \) between UE \( l \) and MBS
is given by [11]

\[
h_l = g_l R_l^R \sqrt{G \cdot A_l(\varphi, \theta) \cdot PL(d_l) \cdot Z_l \cdot \alpha_l} \quad (5)
\]

where \( g_l \sim \mathcal{CN}(0, I_K) \) are independent fast fading channel
vectors and \( P_G \) represents propagation gain consisting of the

Figure 1. A two-tier network architecture consisting of one
macro-cell and \( S \) virtual small cells.
MBS antenna gain $G$, the antenna pattern $A_i(\varphi, \theta)$, path loss $PL_i$, the log-normal shadowing $Z_i$ and the small-scale fading $\alpha_i$. Using the physical channel model in [12], channel covariance matrix $R_l^h = [A \ 0_{NBS \times NBS} - N_P] \in \mathbb{C}^{NBS \times NBS}$ can be obtained, where $N_P$ is the physical dimensions and the spatial correlation matrix $A \in \mathbb{C}^{NBS \times NBS}$ is composed of the steering vectors $a(\varphi, \theta) \in \mathbb{C}^{NBS}$. Note that the channel model is related with antenna pattern and steering, which might be adapting to the changes of VSCs.

III. ADAPTIVE BEAMFORMING DESIGN FOR VSC

A. Problem Formulation

Consider the downlink communication in the cellular network shown in Fig.1. The received signal $y_l$ at the $l$-th user is given by

$$y_l = h_l^H \sum_{i=1}^{L} w_i x_i + n_i,$$

where $x_i \sim \mathcal{CN}(0, 1)$ is the information symbols from the MBS to user $l \in \{1, \ldots, L\}$, $w_i \in \mathbb{C}^{NBS}$ represents the beamforming vectors and $n_i$ is the white additive Gaussian noise with zero-mean and variance $\sigma_l^2 \leq 0$. With single-user detection, the signal-to-interference-and-noise ratio (SINR) of user $l$ can be expressed as

$$SINR_l = \frac{|h_l^H w_l|^2}{\sum_{i=1, i \neq l}^{L} |h_l^H w_i|^2 + \sigma_l^2}.$$  

The first term of the denominator of above equation is the co-channel interference. Compared with the traditional small cell, the VSC can reduce the inter-cell interference because the intra-cell communication is in the unlicensed band.

The total power consumption of per subcarrier in Eq. (8) is consisting of two terms: the term of $P_b$, which is related to the hardware design of MBS/CHs and the term of $P_h$, depending on the beamforming design [13].

$$P_b = \rho_0 \sum_{i=1}^{L} ||w_i||^2,$$

$$P_h = \frac{\xi_0}{C} NBS + \sum_{j=1}^{S} \frac{\xi_j}{C} N_{CH},$$

$$P_l = P_b + P_h,$$

where $1/\rho_0$ is the efficiency of power amplifiers, $C$ is the total number of subcarriers and $\xi_j$ represents the circuits power consumption of each antenna at MBS/CH. From Eq. (8), we can see that only $L$ ($S \leq L < K$) users connect with MBS and thus MBS can focus more energy beamforming with each user.

The adaptive beamforming design is optimized to achieve the minimum total power consumption under the target rate requirement of each user and transmitted power consumption constraint of MBS. Therefore, the adaptive beamforming design of VSCs can be formulated as an optimization problem:

$$\min_{W_l \forall l} \quad \rho_0 \sum_{l=1}^{L} ||W_l||^2 + P_h,$$

subject to

$$\log_2(1 + \frac{|h_l^H w_l|^2 \sum_{i=1, i \neq l}^{L} |h_l^H w_i|^2 + \sigma_l^2}) \geq \gamma_l \forall l,$$

$$\sum_{l=1}^{L} w_l^H w_l \leq P_{\text{max}} \forall l,$$

where the $P_{\text{max}}$ is the total power constraints at MBS. The optimization problem in Eq. (9) is not convex as we will show in the next Section. In general, non-convex optimization problems are hard to solve in polynomial time.

B. Semi-definite Relaxation

By defining correlation matrix $W_l = w_l w_l^H$, the original problem in Eq. (9) can be rewritten as

$$\min_{W_l \forall l} \quad \rho_0 \sum_{l=1}^{L} \text{tr}(W_l) + P_h,$$

subject to

$$h_l^H \left( \left(1 + \frac{1}{\gamma_l} W_l \right) - \sum_{i=1, i \neq l}^{L} W_i \right) h_l \geq \sigma_l^2 \forall l,$$

$$\sum_{n=1}^{L} \text{tr}(W_l) \leq P_{\text{max}} \forall l,$$

$$W_l \succeq 0 \forall l,$$

Due to rank-one constraint, optimization problem Eq. (10), which is equivalent to Eq. (9), is not a convex optimization problem. By removing rank constraint $\text{rank}(W_l) = 1$, the relaxed version of the original problem in Eq. (10) is convex, which can be solved by using conventional alternative iteration method [14]. However, it is difficult to prove that there always exist an optimal solution that satisfies the rank-one constraint in theory. An optimizer of the relaxed version of Eq. (10), $W_l^*, l = 1, \ldots, L$, with $\text{rank}(W_l^*) > 1$, for any $l$, only provides an upper bound on the optimal value of the optimization problem given by Eq. (9). To guarantee the rank constraint, a diagonal matrix $B_l \in \mathbb{C}^{NBS \times NBS}$ is introduced and the problem of Eq. (10) can be reformulated

$$\min_{W_l \forall l} \quad \rho_0 \sum_{l=1}^{L} \text{tr}(B_l W_l) + P_h,$$

subject to

$$h_l^H \left( \left(1 + \frac{1}{\gamma_l} W_l \right) - \sum_{i=1, i \neq l}^{L} W_i \right) h_l \geq \sigma_l^2 \forall l,$$

$$\sum_{n=1}^{L} \text{tr}(W_l) \leq P_{\text{max}} \forall l,$$

$$W_l \succeq 0 \forall l.$$
where $B_l = b_l I_{N_{BS}}$. The basic idea of the proposed method is to adjust $b_l$ to make the solution of rank-one. The problem of Eq. (11) is equivalent to the problem of Eq. (10) by setting $b_l = 1$ at the beginning. If any rank of $W_l$ is larger than one, the value of $b_l$ is increased iteratively to reduce the entries of $W_l$. Because of the same constraints, the optimal solution of $W_l$ in Eq. (11) is suitable for Eq. (10). The process of the modified semi-definite relaxation is provided in Algorithm 1.

**Algorithm 1 Modified Semi-definite Relaxation Algorithm**

1: **input**: $N_{BS}$, threshold $T_b > 0$, scalar $\beta > 1$, $h_l$ and $\gamma_l$ for all $l \in L$
2: **Initialize** $b_l = 1$ for all $l \in L$
3: Set $B_l \leftarrow b_l I_{N_{BS}}$
4: Solve the problem of Eq. (11) to get the $W_l$ by using traditional alternative iteration solution.
5: if the rank of all $W_l$ equal to one then
6: Exit
7: else
8: while $b_l < T_b$ do
9: Set $b_l \leftarrow \beta b_l$
10: end while
11: end if
12: output $W$

In Algorithm 1, $\beta > 1$ denotes the step size of iteration and $T_b$ is the threshold. These values should be selected carefully to find a trade-off between the number of iteration and the effect of rank constraint.

### C. Low Complexity Optimization Algorithm

However, the computational complexity of the optimization algorithm grows significantly with the number of users $K$ and the number of antennas $N$. To reduce the complexity, we should divide the original optimization problem into two parts and consider the constraint of throughput rate constraint first. To extract the hidden convexity of throughput rate constraint, we assume that

$$\sqrt{|h_l^H w_l|^2} = h_l^H w_l \geq 0.$$  

The constraint $SINR_l \geq \tilde{\gamma}_l$, $\tilde{\gamma}_l = 2^{\gamma_l} - 1$ can be rewritten as [15]

$$\frac{1}{\gamma_l \sigma_l^2} |h_l^H w_l|^2 \geq \sum_{i \neq l} \frac{1}{\sigma_l^2} |h_l^H w_i|^2 + 1,$$

$$\frac{1}{\sqrt{\gamma_l \sigma_l^2}} R(h_l^H w_l) \geq \sqrt{\sum_{i \neq l} \frac{1}{\sigma_l^2} |h_l^H w_i|^2 + 1}. \quad (12)$$

The SINR constraint in Eq. (12) can be reformulated as a second-order cone constraint and hence, strong duality and the Karush-Kuhn-Tucker (KKT) conditions can be used to solve the optimal problem. The Lagrangian function associated with Eq. (9), only considering the first constraint, is defined as

$$\mathcal{L}(w_1, \cdots w_L, \lambda_1, \cdots \lambda_L) = \sum_{i=1}^L |w_i|^2 + P_h,$$

$$+ \sum_{i=1}^L \lambda_l \left( \sum_{i \neq l} \frac{1}{\gamma_l \sigma_l^2} |h_l^H w_i|^2 + 1 - \frac{1}{\gamma_l \sigma_l^2} |h_l^H w_l|^2 \right),$$

where $\lambda_l \geq 0$ is the Lagrange multiplier vector. For a given optimal $\lambda$, the KKT conditions is given by

$$w_l + \sum_{i \neq l} \frac{\lambda_l}{\gamma_l \sigma_l^2} h_l^H w_i - \frac{\lambda_l}{\gamma_l \sigma_l^2} h_l^H w_l = 0,$$

$$\Leftrightarrow w_l = \left( I + \sum_{i=1}^L \frac{\lambda_l}{\gamma_l \sigma_l^2} h_i^H h_i \right)^{-1} h_l \frac{\lambda_l}{\gamma_l \sigma_l^2} \left( 1 + \frac{1}{\gamma_l} \right) h_l^H w_l,$$

$$\Leftrightarrow w_l^* = \sqrt{p_l} \left( I + \sum_{i=1}^L \frac{\lambda_l}{\gamma_l \sigma_l^2} h_i^H h_i \right)^{-1} h_l$$

$$= (\text{beamforming power}) \left( I + \sum_{i=1}^L \frac{\lambda_l}{\gamma_l \sigma_l^2} h_i^H h_i \right)^{-1} h_l.$$

Eq. (14) is the first order optimality conditions of beamforming, consisting of beamforming power $p_l$ and beamforming direction $w_l^*$. To reduce the complexity, equal power allocation scheme can be used to find the beamforming direction first. Therefore, substituting $\lambda_l = \frac{P_{t,\text{max}}}{L}$ into Eq. (14), the optimal beamforming direction can be obtained by

$$w_l = \frac{h_l \left( \sum_{i=1}^L \frac{1}{\gamma_l} h_i^H h_i + \frac{L}{P_{t,\text{max}}} I \right)^{-1}}{\left\| h_l \left( \sum_{i=1}^L \frac{1}{\gamma_l} h_i^H h_i + \frac{L}{P_{t,\text{max}}} I \right)^{-1} \right\|} \cdot \quad (15)$$

The Eq. (15) illustrates that the optimal beamforming directions can be found by maximizing the ratio of the desired signal power to the noise power and minimizing the interference caused by co-channel users. In fact, this is equal to the concept of maximizing signal-to-leakage-and-noise ratio (Max-SLNR) beamforming, which is a kind of heuristic beamforming methods and is non-iterative [16]. Then, Eq. (9) can be rewritten as an optimization problem of power allocation

$$\min_{p_1 \cdots p_L} \sum_{l=1}^L p_l + P_h,$$

subject to

$$\sum_{l=1}^L p_l \leq P_{t,\text{max}} \forall l,$$

$$p_l \cdot |h_l^H w_l^*|^2 \left( 1 + \frac{1}{\gamma_l} \right) \geq \sum_{i=1}^L p_i \cdot |h_i^H w_l^*|^2 \geq \sigma_l^2 \forall l.$$
The optimal power allocation $p_l^*$ can be obtained by solving the above convex optimization problem and should be sent to MBS to calculate the final optimal beamforming. The proposed low-complexity algorithm is summarized in Algorithm 2.

**Algorithm 2 Low-complexity Algorithm**

1: **input**: $N_{BS}$, $h_l$ and $\tilde{\gamma}_l$ for all $l \in L$
2: **Initialize** $w_l$ for all $l \in L$
3: **Step 1**:
4: for user form 1 to $L$ do
5: each user calculates the optimal beamforming direction with equal power allocation
6: $\tilde{w}_l = h_l \left( \sum_{i=1}^{L} \frac{1}{\sigma_i^2} h_i h_i^H + L P_{t,max} I \right)^{-1} \|h_l \left( \sum_{i=1}^{L} \frac{1}{\sigma_i^2} h_i h_i^H + L P_{t,max} I \right)^{-1} \|$
7: end for
8: **Step 2**: Compute the optimal power allocation $p_l^*$ by solving the convex optimization problem of Eq. (16).
9: **Step 3**: $w_l = \sqrt{p_l^*} \tilde{w}_l$ for all $l \in L$
10: **output**: $w$

**IV. SIMULATIONS**

In this section, link level simulation is conducted using Monte Carlo methods in order to evaluate the performance of the proposed scheme of the virtual small cell and the proposed adaptive beamforming algorithms. Consider a two-tier networks consisting of one macro cell and five VSCs, where 30 users are randomly distributed. Other main parameters that are used to model channel and power consumption are given in Table I according to [17] and [18].

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efficiency of power amplifiers of BS</td>
<td>0.388</td>
</tr>
<tr>
<td>Efficiency of power amplifiers of CH</td>
<td>0.06</td>
</tr>
<tr>
<td>Circuit power of per antenna at BS</td>
<td>189 mW</td>
</tr>
<tr>
<td>Circuit power of per antenna at CH</td>
<td>5.6 mW</td>
</tr>
<tr>
<td>Power constraints of per-antenna for BS</td>
<td>66 mW</td>
</tr>
<tr>
<td>Power constraints of per-antenna for CH</td>
<td>0.08 mW</td>
</tr>
<tr>
<td>Macro cell radius</td>
<td>0.8</td>
</tr>
<tr>
<td>Small cell radius</td>
<td>0.08 km</td>
</tr>
<tr>
<td>Standard deviation of log-normal shadowing</td>
<td>7 dB</td>
</tr>
<tr>
<td>Path and penetration loss for macro-cell</td>
<td>$148.1 + 37 \log_{10}(d)$ dB</td>
</tr>
<tr>
<td>Path and penetration loss for small cell</td>
<td>$127 + 30 \log_{10}(d)$ dB</td>
</tr>
<tr>
<td>Noise variance</td>
<td>-127 dBm</td>
</tr>
<tr>
<td>Noise figure</td>
<td>5 dB</td>
</tr>
</tbody>
</table>

Fig. 2 shows the virtual small cell formation using clustering algorithm and the define of the cell center/ radius. 100 users are generated randomly in an area, and K-MEANS clustering algorithm is executed as an example for the virtual small cell clustering procedure [7]. It can be seen in the figure that users are grouped as blue and red as fist step and the cell center is decided. Afterwards, far users are removed from the virtual cells using average distance plus standard deviation. In order to find the radius of virtual small cells, the transmission range of IEEE 802.11p protocol is applied, and the smaller value between the transmission range and average distance plus standard deviation would be the virtual small radius.

Fig. 3 illustrates the total power consumption of three scenarios with different number of antennas ($N_{BS}$ and $N_{CH}$), while the bit rates requirement of each user is 2 bits/s/Hz. The optimal beamforming algorithm has been elaborated in Section III-B, and the solution of the convex optimization problem is obtained using the modeling language CVX in simulation [19]. In terms of traditional small cell scenario, soft cell [20] is applied, where each user communicates with any combination of transmitters (MBS and SCAs). As can be seen from Fig. 3, the average total power consumption decrease dramatically with the increase in antenna numbers at the MBS and CH. The reason is that the increase in the diversity gain outweighs the increase in the hardware cost $P_h$. This situation bottomed out...
at $N_{BS} = 40 - 60$ and the total power then starts to increase slowly. Moreover, it is predicted that more power consumption is needed in the scenario of macro-only than that of SCs in order to achieve the same rate target. To reduce the optimization complexity, beamforming direction can be selected for equal power allocation first. After this step, the original optimization problem can be reformulated as a simple convex optimization problem of power allocation. The optimal and sub-optimal solutions of beamforming design are analyzed. Both mathematical and simulation results demonstrate that compared with scenarios of only BS and soft small cells, VSCs can improve the energy efficiency dramatically with better energy-focusing and less inter-cell interference.

**REFERENCES**


