

**Content-Centric Multicast Beamforming in Cache-Enabled Cloud Radio Access Networks**

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**Abstract**—Multicast transmission and wireless caching are effective ways of reducing air and backhaul traffic load in wireless networks. This paper proposes to incorporate these two key ideas for content-centric multicast transmission in a cloud radio access network (RAN) where multiple base stations (BSs) are connected to a central processor (CP) via finite-capacity backhaul links. Each BS is equipped with multiple antennas and a cache with finite storage size. The BSs cooperatively transmit contents, which are either stored in the local cache or fetched from the CP, to multiple users in the network. Users in the same multicast group receive the common contents from the same cluster of BSs using the same beamformers, while different multicast groups receive independent contents. Assuming fixed cache placement, this paper investigates the joint design of multicast beamforming and content-centric BS clustering by formulating an optimization problem of minimizing the total network cost under the quality of service (QoS) constraints for each multicast group. The network cost involves both the transmission power and the backhaul cost. We model the backhaul cost using the mixed \(l_0/l_2\)-norm of beamforming vectors. To solve this mixed-integer problem, we first approximate using the semidefinite relaxation (SDR) method and concave smooth functions. We then propose a difference of convex (DC) programming algorithm to obtain suboptimal solutions and show the connection of three smooth functions. Simulation results validate the advantage of multicasting and show the effects of different cache size and caching policies in Cloud RAN.

**I. INTRODUCTION**

Cloud radio access network (RAN) is an emerging network architecture capable of exploiting the advantage of multicell cooperation in the future fifth-generation (5G) wireless system [1]. In Cloud RAN, the base-stations (BSs) are connected with a central processor (CP) via digital backhaul links, thus enabling joint data processing and precoding capabilities across multiple BSs. This paper proposes a content-centric view for Cloud RAN design. We equip the BSs with finite-size cache, where popular contents desired by multiple users can be stored. We formulate and solve a network optimization problem while accounting for the finite-capacity backhaul links between the BSs and the CP.

To address the issue of limited backhaul, previous works on wireless cooperative networks [2] [3] [4] consider the problem of minimizing the backhaul traffic and transmission power by designing sparse beamformer and user-centric BS clustering. Further, [5] considers the weighted sum rate (WSR) optimization problem under per-BS backhaul constraints. However, all these works focus on the unicast scenario and promote a user-centric view of system design in non-cache networks.

Recently, wireless caching has been investigated as an effective way of reducing peak traffic and backhaul load. By deploying caches at BSs and placing popular contents in them in advance, the issue of limited backhaul capacity can be addressed fundamentally. In [6], the authors show that with small or even no backhaul capacity, femtocaching can support high demand of wireless video distribution. In [7], the upper and lower bounds of the capacity of the coded-caching system are derived, and it shows that the network capacity could be further improved compared with the uncoded-caching system. These studies motivate us to consider the cache-enabled Cloud RAN, where each BS is equipped with a cache with finite storage size. Compared with non-cache cooperative networks, cache-enabled Cloud RAN can fundamentally reduce the backhaul cost and supports more flexible BS clustering. We note that in [8], a similar wireless caching network has been considered, where the authors study the data assignment and unicast beamforming design.

Different from previous work focusing on unicast scenario [2] [3] [4] [8], where the data is transmitted via unicast to each user individually, no matter whether the actual contents requested by different users are the same or not, this paper focuses on the problem of multicast transmission. We assume that multiple users request the same content, which is delivered using multicast beamforming to these users on the same resource block. Compared with traditional unicast, multicast can improve energy and spectral efficiency. In addition, since the popular contents cached in the BSs are possibly requested by multiple users, multicast could better exploit the potential of wireless caching.

This paper studies the joint design of multicast beamforming and content-centric BS clustering, which differs from the fixed BS clustering in coordinated muticell multicast networks [9] or user-centric BS clustering in unicast systems [3]. In each scheduling interval, the BS clustering is dynamically optimized with respect to each multicast group. We formulate an optimization problem with the objective of minimizing the total power consumption as well as the backhaul cost under the quality of service (QoS) constraints of each multicast group. The backhaul cost is formulated as a function of the mixed \(l_0/l_2\)-norm of the beamforming vectors. The optimization problem is a mixed-integer nonlinear programming problem.
of which is shown in Fig. 1. Each BS is equipped with \( \sum \) and dynamic content-centric BS clustering. Each group \( m \) served by a cluster of BSs cooperatively, denoted as \( \{Q_m\}_{m=1}^M \), where the authors use Gaussian family functions to approximate the \( l_0 \)-norm. The smooth function method is a better approximation to the \( l_0 \)-norm but its performance highly depends on the smoothness factor of the approximation function. In this paper, we adopt the smooth function approach and compare the performance of three smooth functions: logarithmic function, exponential function and arctangent function. The approximated problem is then solved with a difference of convex/concave function (DC) algorithm [12]. To control the smoothness of the smooth function, we define a set of smoothness factors and propose a method to adjust their values dynamically in each DC iteration. Further, we provide some insight into the connection between the three smooth functions, and explain the similar performance between the reweighted \( l_1 \)-norm approach [3] and the smooth function approach [4]. Simulation results are presented to illustrate the performance of proposed algorithm, the power-backhaul tradeoff between unicast and multicast transmission and the benefit of wireless caching.

Notations: Boldface uppercase letters denote matrices and boldface lowercase letters denote column vectors. \( \mathbb{C} \) and \( \mathbb{B} \) stand for the sets of complex number and binary number respectively. \( E(\cdot), (\cdot)^T \) and \( (\cdot)^H \) are the statistical expectation, transpose and Hermitian transpose, respectively. \( \|\cdot\|_2 \) and \( \|\cdot\|_0 \) denote the Frobenius norm and the \( l_0 \) norm respectively. \( \mathbf{1}_M \) and \( \mathbf{0}_M \) denote the \( M \)-long all-ones and \( M \)-long all-zeros vectors respectively. The inner product between matrices \( \mathbf{X} \) and \( \mathbf{Y} \) is defined as \( \langle \mathbf{X}, \mathbf{Y} \rangle = \text{Tr}(\mathbf{X}^H \mathbf{Y}) \). For a square matrix \( \mathbf{S}_{M \times M} \), \( \mathbf{S} \succeq \mathbf{0} \) means that \( \mathbf{S} \) is positive semi-definite.

II. SYSTEM MODEL

A. Signal Model

We consider a cache-enabled Cloud RAN with one CP, \( L \) BSs, \( K \) mobile users and \( M \) multicast groups, an example of which is shown in Fig. 1. Each BS is equipped with \( N_t \) (\( N_t \geq M \)) antennas and each user has a single antenna. All the scheduling and beamformer design are processed in the CP and each BS is connected to the CP via a finite-capacity backhaul link. The CP stores all the files and there is a cache at each BS, which stores finite number of files. Each multicast group \( m \), for \( m = 1, \ldots, M \), serves a set of \( K_m \) users with \( \sum_{m=1}^M |K_m| = K \). Each user belongs to only one group.

We study the cooperative downlink multicast transmission and dynamic content-centric BS clustering. Each group \( m \) is served by a cluster of BSs cooperatively, denoted as \( Q_m \).

In each scheduling interval, the BS clustering \( \{Q_m\}_{m=1}^M \) is dynamically optimized by the CP. For example, in Fig. 1 the instantaneous BS clusters for different groups are \( Q_1 = \{1, 2, 3\} \), \( Q_2 = \{2\} \) and \( Q_3 = \{2, 3\} \), respectively. For BS 1, since it serves group 1, it should acquire the files for group 1 either from its local cache or through backhaul.

We denote the aggregate beamforming vector of group \( m \) from all BSs as \( \mathbf{w}_m \in \mathbb{C}^{LN_t \times 1} = [\mathbf{w}_{1,m}^H, \mathbf{w}_{2,m}^H, \ldots, \mathbf{w}_{L,m}^H]^H \), where \( \mathbf{w}_{l,m} \in \mathbb{C}^{N_t \times 1} \) is the beamforming vector for group \( m \) at BS \( l \). Note that the BS clustering is implicitly defined by the beamforming vectors. If the beamforming vector \( \mathbf{w}_{1,m} \) is \( \mathbf{0}_{N_t} \), then BS \( l \) does not send contents to group \( m \) and is thus not in \( Q_m \). On the contrary, if \( \mathbf{w}_{1,m} \neq \mathbf{0}_{N_t} \), BS \( l \) is part of the serving cluster of group \( m \). This relationship can be modeled with the mixed \( l_0/l_2 \)-norm of beamforming vector \( \mathbf{w}_{l,m} \), given as \( \|\|\mathbf{w}_{l,m}\||_2^2 \|_0 \).

We denote the data symbol of group \( m \) as \( s_m \in \mathbb{C} \), with \( E[|s_m|^2] = 1 \). For user \( k \in \mathcal{K}_m \), its received downlink signal \( y_k \) can be written as

\[
y_k = h_k^H \mathbf{w}_m s_m + \sum_{n \neq m} h_k^H \mathbf{w}_n s_n + z_k, \tag{1}
\]

where \( h_k \in \mathbb{C}^{LN_t \times 1} \) is the network-wide channel vector from all BSs to user \( k \) and \( z_k \sim \mathcal{CN}(0, \sigma^2) \) is the additive noise.

The received signal-to-interference-plus-noise ratio (SINR) at user \( k \in \mathcal{K}_m \) is

\[
\text{SINR}_k = \frac{|h_k^H \mathbf{w}_m|^2}{\sum_{n \neq m} |h_k^H \mathbf{w}_n|^2 + \sigma^2}. \tag{2}
\]

We define the target SINR vector as \( \gamma = [\gamma_1, \gamma_2, \ldots, \gamma_M] \) with each element \( \gamma_m \) being the target SINR to be achieved by the users in group \( m \). In this paper, we consider the fixed rate transmission as in [8], where the transmission rate for group \( m \) is set as \( R_m = \log_2(1 + \gamma_m) \). Thus, to successfully decode the message, for any user \( k \in \mathcal{K}_m \), its achievable
The optimization problem is formulated as
\[
\mathcal{P}_0 : \quad \text{minimize} \quad C_N \quad \text{(5a)}
\]
subject to \( \text{SINR}_k \geq \gamma_m, \forall m, k \in \mathcal{K}_m \) \( \text{(5b)} \)
\[
\sum_{m=1}^{M} \| w_{l,m} \|_2^2 \leq P_l, \forall l \quad \text{(5c)}
\]
where \( P_l \) is the peak transmission power at BS \( l \).

Problem \( \mathcal{P}_0 \) is an MINLP, where the non-convexity comes from both the \( l_0 \)-norm in the objective function and the SINR constraints. Unlike traditional unicast beamforming problems where the non-convex SINR constraints can be transformed to a second-order cone programming (SOCP) problem and the optimal solutions can be obtained with convex optimization, the multicast beamforming problem is NP-hard \( \text{(10)} \). In this paper, we use two techniques to approximate problem \( \mathcal{P}_0 \), namely SDR relaxation and \( l_0 \)-norm approximation. The overall procedure to solve \( \mathcal{P}_0 \) is shown in Fig. 2 with each step elaborated in following sections.

B. Step 1 – SDR Relaxation

In both single-cell \( \text{(10)} \) and multicell \( \text{(9)} \) scenarios, the semidefinite relaxation (SDR) method has been used to deal with the non-convex SINR constraints in multicast beamforming design problems.

We define two sets of matrices \( \{ W_m \in \mathbb{C}^{L_N \times L_N} \}_{m=1}^{M} \) and \( \{ H_k \in \mathbb{C}^{L_N \times L_N} \}_{k=1}^{K} \) as
\[
W_m = \omega_m w_m^H \quad \text{and} \quad H_k = h_k h_k^H, \quad \forall m, k. \quad \text{(6)}
\]
We further define a set of selective matrices \( \{ J_l \}_{l=1}^{L} \), where each matrix \( J_l \in \mathbb{B}^{L \times L_N \times L_N} \) is a diagonal matrix defined as
\[
J_l = \text{diag} \left( [0_{(l-1)N_l}, 1_{N_l}, 0_{(L_l-l)N_l}] \right), \quad \forall l. \quad \text{(7)}
\]
Therefore, for \( \forall l, m \), we have
\[
\| w_{l,m} \|_2^2 = \text{Tr}(W_m J_l) \quad \text{(8)}
\]
By adopting the SDR method, problem \( \mathcal{P}_0 \) can be relaxed and rewritten as
\[
\mathcal{P}_{SDR}:
\]
\[
\text{minimize} \quad \sum_{m=1}^{M} \left\| \sum_{l=1}^{L} \left( \sum_{m=1}^{M} \alpha_{l,m} \text{Tr}(W_m J_l) \right) \right\|_0 \quad \text{(9a)}
\]
subject to \( \text{Tr}(W_m H_k) \quad \sum_{m \neq m}^M \text{Tr}(W_m H_k) + \sigma^2 \geq \gamma_m, \forall m, k \in \mathcal{K}_m \) \( \text{(9b)} \)
\[
\sum_{m=1}^{M} \text{Tr}(W_m J_l) \leq P_l, \quad \forall l \quad \text{(9c)}
\]
\[
W_m \succeq 0, \quad \forall m \quad \text{(9d)}
\]
where, to further simplify the mathematical representation, we define a set of constants \( \{ \alpha_{l,m} \}_{l=1, \ldots, L} \) with \( \alpha_{l,m} = R_m (1 - c_{l,m}) \).
The SINR constraints in problem $P_{SDR}$ are convex. We denote the resulting optimal $\{W^*_m\}$ after solving problem $P_{SDR}$ as $\{\hat{W}^*_m\}$. If for each $W^*_m$ in $\{\hat{W}^*_m\}$, it is already rank-one, then for group $m$ the optimal aggregate beamformer $\hat{w}^*_m$ of problem $P_0$ can be obtained by applying eigen-value decomposition (EVD) to $W^*_m$, as $W^*_m = \lambda^*_m \hat{w}^*_m \hat{w}^*_m H$. Otherwise, the beamforming vectors $\{\hat{w}^*_m\}$ can be generated with the randomization method used in [9] and [10].

C. Step 2 – $l_0$-norm Approximation

To solve problem $P_{SDR}$, we further approximate the non-convex $l_0$-norm in the objective with a continuous function denoted as $f(X)$. Specifically, we consider three kinds of concave smooth functions: logarithmic function, exponential function and arctangent function [13], defined as

$$f(X) = \begin{cases} \log \left( \frac{\text{Tr}(X) + \theta}{\theta} \right), & \text{for log-function} \\ 1 - e^{-\frac{\text{Tr}(X)}{2}}, & \text{for exponential-function (10)} \\ \arctan \left( \frac{\text{Tr}(X)}{\theta} \right), & \text{for arctangent-function} \end{cases}$$

where $\theta$ is a parameter to adjust the smoothness of the functions. In all three cases, with larger $\theta$, the function is smoother but is a worse approximation to the $l_0$-norm.

In [4], the authors use the Gaussian family smooth functions, where the $l_0$-norm of $\|w\|_2$ is approximated with $f(\|w\|_2) = 1 - \exp(-\frac{\|w\|_2^2}{2\theta^2})$. In this work, by adopting the exponential smooth function, the $l_0$-norm is approximated with $f_{\exp}(W) = 1 - \exp(-\frac{\text{Tr}(W)}{\theta})$. Comparing $f(\|w\|_2)$ and $f_{\exp}(W)$, we can see that the exponential smooth function in (10) has the same approximation effect as the Gaussian smooth function in [4]. However, different from $f(\|w\|_2)$, $f_{\exp}(W)$ is a concave function about $W$ and can thus be solved with the DC algorithm, which will be introduced in the next section.

With smooth function $f(X)$, $P_{SDR}$ can be rewritten as $P_{SF}$:

$$\begin{align} P_{SF} : \quad & \text{minimize} \quad \sum_{m=1}^{M} \eta \text{Tr}(W_m) + \sum_{m=1}^{M} \sum_{l=1}^{L} \alpha_{l,m} f(W_m J_l) \\ & \text{subject to} \quad (9a), (9b), (9d). \end{align}$$

(11a) (11b)

For ease of presentation, we express the objective as the summation of two functions $G(W)$ and $F(W)$, defined as

$$G(W) = \sum_{m=1}^{M} \eta \text{Tr}(W_m) \quad \text{and} \quad F(W) = \sum_{m=1}^{M} \sum_{l=1}^{L} \alpha_{l,m} f_{l,m},$$

(12)

where $f_{l,m} = f(W_m J_l), \forall l, m$.

We see that $G(W)$ and $F(W)$ are an affine and a concave function of $W$, respectively. Therefore, problem $P_{SF}$ can be viewed as the difference of two continuous convex functions with convex constraints. Therefore, this problem can be solved with the DC algorithm, which falls in the category of majorization-minimization (MM) algorithms [12].

IV. DC Based Algorithm and Analysis

In this section, we first present the DC based algorithm to solve problem $P_{SF}$. Then, we propose a method to iteratively adjust the smoothness factor $\theta$. Finally, we discuss the effects of three different smooth functions and give some insight into their connection.

A. DC Based Algorithm

The DC algorithm iteratively optimizes an approximated convex function of the original concave objective function and produces a sequence of improving $\{W_m\}$. The algorithm converges to some global/local optimal solution.

The initial solution $W_m^{(0)}$ is initialized by solving the following power minimization problem

$$P_{ini} : \quad V_{ini} \triangleq \min W_m^{(0)} \sum_{m=1}^{M} \text{Tr}(W_m) \quad \text{subject to} \quad (9a), (9b), (9d).$$

(13a) (13b)

In the $t$th iteration, the $W_m^{(t)}$ is generated as the solution of the approximated convex optimization problem,

$$P_t : \quad V_t \triangleq \min W_m^{(t-1)} G(W) + \sum_{m=1}^{M} \sum_{l=1}^{L} \alpha_{l,m} \left( \langle \nabla W_m^{(t-1)} \tilde{f}_{l,m}, W_m - W_m^{(t-1)} \rangle \right) \quad \text{subject to} \quad (9a), (9b), (9d).$$

(14a) (14b)

where $\nabla W_m^{(t-1)} \tilde{f}_{l,m}$ is the gradient matrix of $f_{l,m}$ at $W_m^{(t-1)}$.

Notice that the value of $\nabla W_m^{(t-1)} \tilde{f}_{l,m}$ is related to the smoothness factor $\theta$. Instead of using a common $\theta$ for all $f_{l,m}$ as in [4], we define a set smoothness factors $\{\theta_{l,m}\}_{l=1, \ldots, L}$, where each element $\theta_{l,m}$ is the smoothness factor of $f_{l,m}$.

In order to expedite convergence, we propose to update $\theta_{l,m}$ in each iteration, such that $\nabla W_m^{(t-1)} \tilde{f}_{l,m}$ is maximized. In iteration $t$, for $\forall l, m$, $\theta_{l,m}$ is updated with

$$\theta_{l,m}^* = \arg \max_{\theta_{l,m}} \nabla W_m^{(t-1)} \tilde{f}_{l,m}.$$
algorithm terminates when the sequence of \( \{W_m(t)\} \) converges to some stationary point, and the objective value \( V_t \) converges, that is, \( V_{t-1} - V_t < \varrho \), where \( \varrho \) is a small constant.

**B. Smooth Function**

The performance of the algorithm depends on the choice of the smooth function \( f(X_t) \), especially its gradient. In the following, we derive the optimal update strategy of \( \{\theta_{l,m}\} \) in (15) for each of the three smooth functions and show the connection between them.

1) **Logarithmic Function**: The logarithmic smooth function is defined as

\[
f_{l,m} = \log \left( \frac{\text{Tr}(W_m J_l) + \theta_{l,m} + \epsilon}{\theta_{l,m}} \right), \quad (16)
\]

and its gradient matrix \( D(l,m) \in \mathbb{C}^{L_N \times L_N} \) at \( \{W_m(t)\} \) is

\[
D(l,m) = \nabla\nabla f_{l,m} = \frac{J_l}{\text{Tr}(W_m J_l) + \theta_{l,m} + \epsilon}, \quad (17)
\]

where \( \epsilon \) is a small factor to avoid division by zero with a value chosen as \( \epsilon = \max\{\min_{m} \text{Tr}(W_m J_l), \tau\} \) and \( \tau \) is some small positive constant. Note that when \( \theta_{l,m} = 0 \), the gradient matrix is maximized in each element.

2) **Exponential Function**: The exponential smooth function is defined as

\[
f_{l,m} = 1 - e^{-\frac{\text{Tr}(W_m J_l) + \epsilon}{\theta_{l,m}}}, \quad (18)
\]

and the maximum gradient matrix of \( f_{l,m} \) at \( \{W_m(t)\} \) is

\[
D^*_{\epsilon}(l,m) = \max_{\theta_{l,m}} \nabla f_{l,m} = \frac{J_l}{1 + 37 \frac{1}{2} \text{Tr}(W_m J_l) + \epsilon}, \quad (19)
\]

with \( \theta^*_{l,m} = \text{Tr}(W_m J_l) + \epsilon \).

3) **Arctangent Function**: Similarly, the arctangent smooth function is defined as

\[
f_{l,m} = \arctan \left( \frac{\text{Tr}(W_m J_l) + \epsilon}{\theta_{l,m}} \right), \quad (20)
\]

and the maximum gradient matrix of \( f_{l,m} \) at \( \{W_m(t)\} \) is

\[
D^*_{\epsilon}(l,m) = \max_{\theta_{l,m}} \nabla f_{l,m} = \frac{J_l}{2 \left( \text{Tr}(W_m J_l) + \epsilon \right)}, \quad (21)
\]

with \( \theta^*_{l,m} = \frac{1}{\text{Tr}(W_m J_l) + \epsilon} \).

In (17), when \( \theta_{l,m} = 0 \), the log-function has the largest gradient, which has the same form as the weights of the reweighted \( l_1 \)-norm approach in [11]. Therefore, the reweighted \( l_1 \)-norm method can be viewed as an approach that first approximates the \( l_0 \)-norm with the logarithmic smooth function and then solves the approximated problem with the MM algorithm. Further, by observing (17) (19) and (21) carefully, we can see that their maximized gradients have the similar form. They slightly differ by a constant multiple. Thus, the update directions corresponding to all three smoothness functions are essentially the same. This explains the similar performance of the reweighted \( l_1 \)-norm algorithms in [2] [3] and the smooth function approach in [4].

![Fig. 3. Simulation scenario with 7 BSs, 4 multicast groups and 14 mobile users randomly distributed.](image)

**V. SIMULATION RESULTS**

We consider a cache-enabled Cloud RAN covering an area of circle with the radius of 1.2km, where 7 BSs (\( L = 7 \)) are placed in an equilateral triangular lattice with the distance between adjacent BSs of 0.8km. A total number of 14 users (\( K=14 \)) are distributed in this network with uniform distribution. There are 4 multicast groups, and we assume that users in the same group are geographically close. The number of users in each group is \([4, 4, 4, 3, 3]\). We let all BSs have the same cache size, with \( F_l = F, \forall l \). The simulation scenario is depicted in Fig. 3 where we fix the geographical position of all BSs, users and the correspondence between users and groups. The channels between BSs and users are generated with a normalized Rayleigh fading component and a distance-dependent path loss, modeled as \( P_{L}(dB) = 128.1 + 37.6 \log_{10}(d) \) with 8dB log-normal shadowing, where \( d \) is the distance from the user to the BS. The power spectral density of downlink noise is \(-174dBm/Hz\) with the channel bandwidth of 10MHz. The target SINR of each group is \([6dB, 6.5dB, 7dB, 7.5dB]\). Unless specified, the cache size in each BS is \( F = 2 \). We set \( \varrho = 10^{-6} \) and \( \tau = 10^{-7} \). Each simulation result is averaged over 300 channel realizations.

In Fig. 4 we show the effects of wireless caching, including the size of caches and caching policy. We use the exponential smooth function. The random caching refers to the policy where the files are randomly cached, that is, in each BS, the probability that a certain file is cached is 0.5. In the fixed caching policy, every BS only caches the files of group 1 and group 2. The figure shows that random caching can achieve lower backhaul cost in this scenario where the number of users in different groups is similar. Moreover, with larger caches, the backhaul traffic and power consumption can be further reduced. When cache size is \( F=3 \), the backhaul cost can be reduced to almost 0.

In Fig. 5 we compare the performance of different smooth functions with random caching. It shows that the three smooth functions have similar performance. When \( \eta \) is small, which corresponds to backhaul-limited systems, the logarithmic function achieves higher energy efficiency.

In Fig. 6, we compare the power-backhaul tradeoff of multicast and unicast transmission in the same scenario. We
use random caching policy with the cache size $F = 2$. In unicast transmission, users of the same group are served by different beamformers and we use the algorithm proposed in \[1\], where in each iteration, for different beamformers and we use the algorithm proposed in \[3\], where in each iteration, for $\forall k, l$, the weight factor $\rho_k^l$ is set to 0 if the content requested by user $k$ is cached in BS $l$. If multiple users in the same group are served by a same BS, the backhaul cost is counted only once. The figure shows that in the power-limited system, the total power consumption of multicast transmission is about 2dBm less than the unicast scenario. When the total power consumption is 40dBm, the backhaul cost of multicast transmission is almost zero. This is because the BSs with cached content can already provide the required QoS. Therefore, it validates the advantage of caching and multicasting in such a scenario.

VI. CONCLUSION

This paper investigates the joint design of multicast beamforming and content-centric BS clustering in a cache-enabled Cloud RAN. The optimization problem is formulated as minimizing the total network cost, including the power consumption and the backhaul cost, under the QoS constraint of each multicast group. We adopt the SDR method and the smooth function approach, introduced in sparse signal processing, to approximate this MINLP problem as a DC programming problem. We then propose a DC algorithm to obtain sub-optimal solutions with an method of dynamically adjusting the smoothness of the smooth functions. Meanwhile, we compare the performance of three smooth functions and give some insight into their connection. Simulation results show that, compared with unicast transmission, multicast transmission can achieve better power-backhaul tradeoff, and the backhaul cost can be further reduced with larger cache size.

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