Content-Based User Association and MIMO Operation over Cached Cloud-RAN Networks

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Abstract—Cloud radio access network (Cloud-RAN) has been introduced to support ever-growing end-users’ needs. To reduce the backhaul traffic and aid coordinated multi-point (CoMP) transmission, base station (BS)-level caching technique can be utilized, where popular contents are pre-fetched at each BS. In this paper, multiple-input-multiple-output (MIMO) operation and user association policy are linked to the underlying cache placement strategy to ensure a good trade-off between load balancing and backhaul traffic taking into account the underlying wireless channel and the finite cache capacity at BSs. Due to the coupled interference among mobile stations, the binary nature of the underlying cache placement and user association matrices, the resulting mixed-timescale mixed integer optimization problem is nonconvex and NP-hard. To solve this problem, we decompose the joint optimization problem into a long-term content placement sub-problem and a short-term content delivery sub-problem. A novel iterative algorithm is introduced by leveraging the alternating direction method of multipliers together with a stochastic parallel successive convex approximation-based algorithm. The introduced scheme enables all BSs to update their optimization variables in parallel by solving a sequence of convex subproblems. Simulation evaluation demonstrates the efficiency of our strategy.

Index Terms—Cloud-RAN, coordinated multi-point transmission, wireless big data, cache placement, user association, cache size constraint, nonconvex optimization.

I. INTRODUCTION

The big data era is being shaped with the ongoing growth of commercial data services, with mobile wireless network constituting a major data source contributor. Nowadays, wireless communication is becoming tightly integrated in our daily lives; especially with the global spread of laptops, tablets, smartphones, video streaming and online social networking applications. This globalization has paved the way to dramatically increase wireless network dimensions in terms of subscribers and the amount of flowing data. In terms of numbers, Cisco Systems forecasts that the number of mobile-connected devices per capita will reach 1.5 by 2021 and global mobile data traffic will increase sevenfold between 2016 and 2021 [1]. The volume, velocity, and variety of data from both mobile users and communication networks follows an exponential increase pattern. Consequently, big data will be further entrenched in the upcoming fifth-generation (5G) wireless networks.

The two important fundamental requirements for the future 5G wireless networks are the ability to support high data traffic and exceedingly low latency [2]. A likely candidate to fulfill these requirements is a Cloud Radio Access Network (Cloud-RAN). The network architecture of Cloud-RAN meets the tremendous increase in data traffic while improving network throughput and energy efficiency for future networks [3]. This architecture spreads several low-cost low-power Base Stations (BSs) all over a small area as an alternative to a high-power BS [2]. In order to have efficient resource allocation and interference management among multiple BSs, digital backhaul links connect all these low-power BSs to a central computing unit (cloud). Since one of the fundamental requirements for 5G wireless networks is the ability to support exceedingly low latency, establishing backhaul links with low latency is necessary [2]. High-speed fiber cables can achieve this requirement at the expense of an increase in infrastructure cost. Using limited-capacity backhaul links can save cost; however, these links may result in higher latency and thus, the overall performance would be lower than that of a network with high-capacity backhaul link. Therefore, the problem of interest in Cloud-RANs is providing a new technique which can support low latency in a low-cost manner.

More recently, researchers have investigated that wireless caching is an effective way to address this issue. Caching capacity at the BS is a new type of wireless network resource. The low-cost, low-complexity, and tight integration with big data analytical tools of wireless caching will help shape future wireless big data processing. However, research on cache-enabled wireless networks is still in its infancy. The main idea behind wireless caching is equipping the BSs with inexpensive limited-size local storage units, and placing the most popular contents in them to create more Coordinated Multi-Point (CoMP) transmission opportunities while serving the users [4]. To do so, a cluster of BSs is assigned to each user to effectively relieve the backhaul capacity demand at the Cloud-RAN. The cutback in backhaul utilization is because of the reduced payload data transmission throughout the backhaul which is due to employing the caching capacity at each BS. Each cluster is formed by aggregating the BSs whose transmission strategies cooperatively serve the UEs within the cluster through joint proceeding [4]. If the user’s serving BSs cache the content that the user requests, it will be transmitted directly by the serving BSs, thereby reducing delivery latency.
as well as backhaul overhead. Otherwise, the content needs to be fetched into the serving BSs’ caches from the cloud via the backhaul link. In such a model, by downloading the most popular content during off-peak hours and serving users from the cache during peak hours, aside from reducing the capacity requirement of backhaul links as well as the delivery from the cache during peak hours, aside from reducing the most popular content during off-peak hours and serving users via the backhaul link. In such a model, by downloading the to be fetched into the serving BSs’ caches from the cloud as well as backhaul overhead. Otherwise, the content needs to be fetched into the serving BSs’ caches from the cloud.

In order to entirely utilize the benefit of wireless caching and to fully exploit the opportunity of serving users through a CoMP transmission, developing advanced caching placement strategies in Cloud-RANs is required. One way to increase the possibility for a user to access its desired content locally is designing the caching contents following some data popularity distribution, such as the Zipf distribution. Moreover, user association can be regarded as an important consideration of whether a BS caches a content or not. To be specific, BSs might cache files that assigned channels to the particular user are not desirable in terms of the signal strength. In this case, although BSs are clustered to share the requested data and deliver service to a specific user, data transmission is not reliable or high transmit power will be needed. Consequently, allocating the requested files via backhaul to BSs that have good channels to the served users will be unavoidable and such allocation via backhaul will increase the backhaul cost. In a densely deployed wireless network, such as Cloud-RAN, each user can be associated with one or several BSs depending on both content availability and channel condition. As a result, jointly optimizing the user-association policy, caching placement strategy, and beamforming design can enhance the user experience.

A. Related Work

The importance of caching in fifth-generation wireless networks was recognized in [1]. In [8], [9], the authors considered the problem of jointly minimizing the total transmit power and backhaul traffic in wireless cooperative networks under the constraint of each user’s SINR requirements and with respect to the beamforming vectors. Assuming there is a backhaul constraint for each BS, [10] considered a weighted sum rate optimization problem to design the beamforming vectors. Other than these works on unicast, [11], [12] discussed the effect of caching on the multicast beamforming in the Cloud-RAN. However, these works assumed that the cache placement is static, which means the caching placement matrix is fixed and known at the cloud.

In order to improve the efficiency of cache-enabled networks, [2], [13]–[15] conducted an investigation into the design of caching policy. In [13], [14], the caching problem at the small cell BSs was considered, and a caching policy was designed in such a way that the cache-hit-ratio is maximized. In order to minimize the downloading latency, [15] proposed a distributed caching algorithm. The line of works in [13]–[15] are further expanded in [2] for a cache-enabled Cloud-RAN system to take the tradeoff between the transmission power and the backhaul cost into consideration. In [2], the authors defined the network cost of the Cloud-RAN system as a normalized weighted sum and, minimized the network cost with respect to both the beamforming matrix and the cache placement matrix by considering the quality of service (QoS), peak transmission power, and cache capacity constraints. However, these works are only focused on designing the beamforming vectors and cache placement matrix while assuming the user association matrix is given and known at the cloud.

The user association problem that is mainly concerned with load balancing, was discussed in [16], [17]. The key point here is accounting for both wireless channels and the number of UEs connected to each BS. Based on a given caching policy, [18] designed the user association policy in a way that maximizes the average download rate. However, the aforementioned studies did not optimize the user association and cache placement jointly. As a result, the system was led to an inefficient operating point.

Designing jointly the caching strategy and the user association policy in cache-enabled wireless networks is considered in [19]–[24]. In order to minimize the number of requests performed by the macro BSs in a small-cell network, [19] designed a joint data caching and user association policy. To this end, [20] jointly designed user association and video caching policy by minimizing the user experienced delay while taking different quality requirements for each user into account. In order to obtain an optimal tradeoff between the content availability and the load balancing in heterogeneous networks, an online algorithm was proposed in [21]. The complexity analysis of joint user association and cache placement in heterogeneous networks was investigated in [22]. In order to maximize the system throughput in a coordinated small-cell cellular system, the problem of joint designing of caching, user association, and routing is discussed in [23]. Considering distinct users have different wireless channels, [24] jointly designed the caching and user association policy by minimizing the average delay of small cell UEs in a heterogeneous network. The line of these works was further expanded in [25] for a cache-enabled Cloud-RAN network to lessen the backhaul traffic by maximizing a proportional fairness network utility. However, [25] considered a single-input single output (SISO) case in which both UEs and BSs are equipped with a single antenna, and each user is only connected with one BS.

In practice, the cache placement and the content delivery (precoding and user association) usually happen in different timescales. Cache placement usually takes much longer (e.g., days or hours) than that of content delivery (e.g., seconds). Therefore, like [30], we study a mixed-timescale joint optimization, but in this case for content placement and content delivery in the cache-enabled cloud radio access networks to maximize a weighted backhaul-aware network utility function subject to the peak transmission power and cache capacity constraints at all BSs. The cache placement reduces the backhaul consumption and provides more CoMP opportunities. It is adaptive to the long-term popularity of data, therefore, the caching strategy should be adaptive to the channel statistics instead of the instantaneous channel.
realization in each channel coherent time. In contrast, the role of the content delivery is to guarantee delivery of a better average throughput to each user and be adaptive to instantaneous channel state information.

B. Main Contributions

This paper differs from previously mentioned studies particularly in its aim to bring a consideration of caching along with user association and resource allocation. We optimize the tradeoff between backhaul reduction and network throughput by maximizing a weighted backhaul-aware network utility function. Furthermore, we consider multiple real-world factors for effective content caching such as popularity distribution, caching placement from the user perspective, and temporal and spatial locality of the content demand, in order to accommodate challenging use cases with strict quality of service requirements. That is why the original problem and, therefore, the three sub-problems in our paper are completely different from the previous works. The main contributions of this paper can be summarized as follows.

- For the first time, we define and maximize the network throughput as a function of caching placement strategy, user association policy, precoding vectors, probability that a file is requested by a specific user, and the distance from all connected BSs to this specific user.
- We introduce the tradeoff between network throughput and backhaul savings by combining content-based user association, MIMO transmit precoding, and cache placement to boost user experience, and identify the interaction between user association, resource allocation and cache placement for a multi-cluster multi-user cache-enabled Cloud-RAN network.
- To the best of our knowledge, there is no existing study on jointly optimizing the cache placement strategy, the user association policy, and the beamforming design. In this work, we consider a multi-cluster multi-user cache-enabled Cloud-RAN network consisting of different users with distinct file preferences, and jointly optimize the mixed-timescale optimization problem of cache placement, user association, and beamforming matrices, which can result in significant benefit. Due to the coupled interference among UEs and the limited-capacity backhaul link constraints, the mixed-timescale joint optimization of content delivery and content placement is a non-convex optimization problem. Furthermore, the entries of cache placement and user association matrices take binary values, making the optimization problem a mixed integer nonlinear programming, which is an NP-hard problem and non-tractable in practice. Since it is highly unlikely to compute a globally optimal solution in polynomial time, our goal is to obtain a trackable near-optimal solution by developing effective suboptimal algorithms. As a consequence, the joint optimization problem decomposes into a short-term content delivery and a long-term content placement problem. Moreover, by making use of the fact that all constraints are separable, we propose an iterative algorithm that optimizes the cache placement, user association, and beamforming vectors.
- We propose an iterative novel algorithm for multi-cluster multi-user cache-enabled Cloud-RANs by leveraging the stochastic parallel successive convex approximation (SCA)-based method and the alternating direction method of multipliers (ADMM). The original non-convex optimization problem is essentially divided into three subproblems. In designing the optimal content placement, the stochastic SCA approximates this subproblem as a sequence of convex subproblems. The decomposition enables all BSs to update their optimization variables in parallel by solving a sequence of convex subproblems, one for each BS. In order to find the optimal beamformers, each subproblem can be replaced by a novel ADMM form. By solving multiple small-size subproblems, the proposed ADMM allows the updation of each step to take place in parallel. Finally, to design the user association strategy, each subproblem is reformulated as a partially dualized version of the original subproblem. By reducing the complexity, the proposed algorithm is feasible for future wireless big data processing systems.

C. Paper Organization and Notations

The remainder of this paper is organized as follows. In Section II, the system model is described and the main assumptions required for our analysis are introduced. Section III, presents the problem formulation and analysis. Simulation results are presented in section IV. An overview of the results and concluding remarks are presented in Section V.

Notation: Throughout this paper, normal letters are used for scalars. Boldface capital and lower case letters denote matrices and vectors, respectively. The transposition, the Hermitian transposition, and the determinant of a complex matrix $A$ are denoted by $A^T$, $A^H$, and $|A|$, respectively. An $N \times K$ matrix, with ones on its main diagonal and zeros on its off-diagonal entries, is denoted by $I_{N \times K}$, while the identity matrix of size $N$ is simply denoted by $I_N$. An $N \times K$ all-zeros matrix is denoted by $0_{N \times K}$. The sets of complex and real numbers are denoted by $\mathbb{C}$ and $\mathbb{R}$, respectively. A circularly symmetric complex Gaussian random variable (r.v.) is represented by $Z \sim \mathcal{CN}(0, \sigma^2)$, where $X$ and $Y$ are independent and identically distributed (i.i.d.) normal r.v.’s from $\mathcal{N}(0, \frac{1}{2})$. $\mathbb{E}[:]$ represents the expectation operator. The Hadamard product between two matrices $A$ and $B$ is symbolized by $A \odot B$.

II. SYSTEM MODEL AND ASSUMPTIONS

We consider a cache-enabled Cloud-RAN network consisting of one central computing unit (cloud), $B$ base stations (BSs), and $K$ user equipments (UEs) as depicted in Figure 1. Table I summarizes the major notations and symbols used in this paper. The location of the BSs is modeled by a Poisson Point Process (PPP) with density $\lambda_B$ while UEs are distributed around each BS independently and uniformly. We partition the area to $M$ clusters. $|I_i|$ and $|Q_i|$ indicate the number of UEs and BSs in the $i$-th cluster, respectively, where $Q_i \subseteq \{1, 2, \ldots, B\}$, $I_i \subseteq \{1, 2, \ldots, K\}$, $Q_i \cap Q_j = \emptyset$, $I_i \cap I_j = \emptyset$, $\forall i \neq j, i, j \in M \triangleq \{1, 2, \ldots, M\}$. Let $i_k \in M$ and $j \in Q_i$, denote the $j$-th BS in the $i$-th cluster and $i_k \in M$ and $k \in I_i$, indicate the $k$-th user in the $i$-th cluster. BS $i_j$ is equipped with $N_i^r$ transmit antennas and a cache that stores $s_{i_j}$ bits of data while user $i_k$ has $N_i^r$ receive antennas. The channel (propagation) coefficient
between the $i_j$ BS and the $i_k$ user form channel matrix $G_{i_j,i_k} = \sqrt{\beta_{i_k,i_j} H_{i_j,i_k}} \in \mathbb{C}^{N_i \times N_k}$, where $\beta_{i_k,i_j}$ is a large-scale fading coefficient that depends upon the shadowing and distance between the corresponding user and BS. The large-scale fading coefficient denoted by $\beta_{i_k,i_j}$ is the distance between the $i_k$ BS and the $i_j$ BS; $\alpha$ is the path-loss exponent; and $\psi_{i_k,i_j}$ is a log-normal random variable, i.e., the quantity $10 \log_{10} \left( \psi_{i_k,i_j} \right)$ is distributed zero-mean Gaussian with a standard deviation of $\sigma_{\text{shadowing}}$. The small-scale fading coefficients, i.e., elements of $H_{i_j,i_k}$, are modeled as i.i.d. complex Gaussian variables with zero-mean and unit-variance. We further assume a block fading model, where small-scale channels are constant over a few time slots with respect to channel estimation and channel state information feedback procedures. Similarly, we assume that large-scale fading coefficients $\beta_{i_k,i_j}$ stay constant during large-scale coherence blocks. The small-scale and large-scale fading coefficients in different coherence blocks are assumed to be independent. Each BS $i_j$ is connected to the cloud through a finite-capacity backhaul link $B_{i_j}, i \in M, j \in Q$. The cloud has access to the whole data library containing $F$ files, where different contents are independent. Making use of the capacity-limited links restricts the amount of information transfer between the cloud and the BSs. We define $\Pi_i = \{\pi_{i_1}, \ldots, \pi_{i_{\bar{r}_i}}\}$ as the user request profile at the $i$-th cluster, where $\pi_{i_j}$ denotes the index of the requested file by the $i_k$ user. Users can make random requests from a directory of files $F = \{f_1, f_2, \ldots, f_q\}$ where each file $f_n$ has size $f_n$. For the sake of simplicity, we assume that the cache size at any BS is at least large enough to cache any of the files, i.e., $f_n \leq s_{i_k}$ for all $f_n \in F$, $i \in M, j \in Q$. Moreover, we assume that the $i_k$ user makes $q_{i_k}$ requests over a given time interval $T$. Therefore, $q_i = [q_{i_1}, \ldots, q_{i_{\bar{r}_i}}]$ indicates the rates of requests that are made by users in the $i$-th cluster, and we also assume different users in the $i$-th cluster, $i \in M$, may have different file preferences. Assuming $p_{i_k,f_n}$ is the probability that $i_k$ user, $i \in M, i \in I_m$, request file $f_n \in F$, the discrete popularity distribution of files for the UEs in the $i$-th cluster can be indicated as:

$$ F_i = \left[ \begin{array}{c} p_{i_1} \\ \vdots \\ p_{i_k} \\ \vdots \\ p_{i_{\bar{r}_i}} \end{array} \right] = \left[ \begin{array}{c} p_{i_1,f_1} \\ \vdots \\ p_{i_k,f_1} \\ \vdots \\ p_{i_{\bar{r}_i},f_1} \\ \vdots \\ p_{i_1,f_F} \\ \vdots \\ p_{i_k,f_F} \\ \vdots \\ p_{i_{\bar{r}_i},f_F} \end{array} \right] \in [0,1]^{\bar{r}_i \times F} $$

where $p_{i_m,f_n}$ represents the probability that the $m$-th UE in the $i$-th cluster requests the $n$-th file. It is worth noting that the $m$-th row of matrix $F_i$ is a stochastic vector that indicates the discrete probability distribution of the $m$-th user.

Since the file popularity distributions seen at each BS depend on the local file popularities of all connected UEs to the BS [26], this matrix will be different from $\tilde{F}_i$. The popularity distributions at the BSs in the $i$-th cluster, namely $F_i \in [0,1]^{Q_i \times F}$, can be derived as:

$$ F_i = \left[ \begin{array}{c} p_{i_1} \\ \vdots \\ p_{i_k} \\ \vdots \\ p_{i_{\bar{r}_i}} \end{array} \right] = \left[ \begin{array}{c} p_{i_1,f_1} \\ \vdots \\ p_{i_k,f_1} \\ \vdots \\ p_{i_{\bar{r}_i},f_1} \\ \vdots \\ p_{i_1,f_F} \\ \vdots \\ p_{i_k,f_F} \\ \vdots \\ p_{i_{\bar{r}_i},f_F} \end{array} \right] \in [0,1]^{\bar{r}_i \times F} $$

where $p_{i_m,f_n} = \frac{\sum_{j=1}^{\bar{r}_j} a_{i_m,j} q_{i_m,j} p_{i_m,f_n}}{\sum_{k=1}^{\bar{r}_k} a_{i_k,j} q_{i_k,j}}$ denotes the $n$-th file popularity distribution observed at the $j$-th BS in the $i$-th cluster and the denominator is a normalization factor. In practice, by adding up the number of times that the $f_n$ file is requested by users, the value of $p_{i_k,f_n}$ can be computed at the cloud. Moreover, since user behavior is correlated with the previously requested data, $p_{i_k,f_n}$ can provide the information regarding the file popularity of the future requests, and thus it helps to efficiently store the files in caches before a request is made. $D_i \in [0,1]^{Q_i \times |I_k|}$ denotes the user association matrix in the $i$-th cluster, which depicts the connection between the BSs and UEs in the $i$-th cluster.
The user association matrix is structured as

$$D_i = \begin{bmatrix} d_{i1} & \ldots & d_{i|Q_i|} \\ \vdots & \ddots & \vdots \\ d_{i|Q_i|1} & \ldots & d_{i|Q_i||I|} \end{bmatrix}$$

where $d_{mn} = \mathbb{I}(\tilde{r}_{m,n} \geq r$, $\tilde{r}_{m,n}$ is the $mn$-th entry of the wireless downlink rate matrix $\tilde{R}_i \in \mathbb{R}^{[|Q_i|] \times |I|}$ in the $i$-th cluster and represents the available data rate from BS $m$ to user $n$ while $r$ guarantees a certain quality of service so that the $n$-th user would not connect to the $m$-th BS if the wireless link rate between them was below the threshold $r$.

Since the caching capacity is limited, the aim of designing a cache placement strategy is to store the most popular contents such that the BSs can directly serve the majority of UEs' demands. We define the content placement matrix at the $i$-th cluster as $C_i \in \{0,1\}^{F \times |Q_i|}$, where $C_i(f_n, i_j) = 1$ means the $f_n$-th content is stored in the $i_j$ BS and $C_i(f_n, i_j) = 0$ represents the opposite. The caching matrix will be different for different user in one cluster. To be specific, the caching matrix corresponding to the BSs that are associated with UE $i_k$, $i \in \mathcal{M}$ and $k \in \tilde{I}_i$, can be expressed as

$$C_{i_k} = C_i\Lambda(D_i(:, i_k)),$$

where $\Lambda(x)$ is a diagonal matrix formed from vector $x$ and $\Lambda(:,n)$ indicates the $n$-th column of the matrix $\Lambda$. Therefore, the sum of all elements in the $n$-th row of $C_{i_k}$ represents the number of BSs that serve the $i_k$ user and cache the $f_n$-th file. Considering that the cache at $i_j$ BS can only store $s_{i_j}$ bits of data, the following cache size constraint should be fulfilled at BS $i_j$

$$\sum_{n=1}^{F} C_i(f_n, i_j)f_n \leq s_{i_j}, \quad \forall i \in \mathcal{M}, \quad j \in \tilde{Q}_i.$$  \hspace{1cm} (2)

Moreover, the $i_k$ user is able to download the $f_n$-th file from the cache if the following condition is satisfied:

$$\sum_{j=1}^{|Q_i|} d_{i_k,j}C_i(f_n, i_j) > 0; \quad \forall i \in \mathcal{M}, \quad k \in \tilde{I}_i, \quad f_n \in \mathcal{F},$$

otherwise, corresponding links may have backhaul cost to transfer the $f_n$-th file. As a result, by associating each user with the BSs that caches its requested content, the total backhaul reduction of the aforementioned cache-enabled Cloud-RAN can be represented as

$$E\{\sum_{i=1}^{M} \sum_{k=1}^{|\tilde{I}_i|} \sum_{j=1}^{|Q_i|} \mathbb{I}(d_{i_k,j}C_i(f_n, i_j))\} = \frac{M}{2} \sum_{i=1}^{M} \sum_{k=1}^{|\tilde{I}_i|} \sum_{j=1}^{|Q_i|} \sum_{n=1}^{F} \sum_{l=1}^{L} \sum_{m=1}^{M} \sum_{p=1}^{P} \text{Tr}(H_{i_k,i_j}H_{i_k,i_j}^H\psi_{m,i_j}u_{i_k,n}^H \mathbf{H}_{i_k,i_j}^{-1} \psi_{m,i_j}^Hv_{m,i_j}) \times \mathbb{I}(\tilde{r}_{m,n} \geq r),$$

where $\mathbb{I}(\tilde{r}_{m,n} \geq r)$ is the indicator function that the BSs can directly serve the majority of UEs' requests. The received signal $\mathbf{y}_{i_k,f_n}$ from the BSs in $\mathcal{B}_{i_k}$ at the $i_k$ UE, at the same frequency and time, can be expressed as

$$\mathbf{y}_{i_k,f_n} = \mathbf{H}_{i_k,i_j} \mathbf{w}_{i_k,f_n} + \mathbf{n}_{i_k,f_n},$$

where $\mathbf{H}_{i_k,i_j}$ is the channel matrix from the BS $i_k$ to the UE $i_j$, $\mathbf{w}_{i_k,f_n}$ is the transmitted signal from the BS $i_k$ at frequency $f_n$, and $\mathbf{n}_{i_k,f_n}$ is the additive white Gaussian noise (AWGN) at the $i_k$ UE. We assumed that the signals for different users are independent from each other.

In this paper, we treat interference as noise and consider a linear receive beamforming strategy so that the estimated signal is given by $\hat{s}_{i_k} = u_{i_k}^H\mathbf{y}_{i_k,f_n}$. Indeed, each receiver $i_k \in \mathcal{K}_{i_k}$, linearly processes the received signal to obtain $\mathbf{u}_{i_k}^H\mathbf{y}_{i_k,f_n}$, where $\mathbf{u}_{i_k} \in \mathbb{C}^{N_k \times 1}$ denotes the unit-norm post processing filter at receiver $i_k$, i.e., $\|\mathbf{u}_{i_k}\|^2 = 1$.

As mentioned above, the received interference at the $i_k$-th UE is the summation of the intra-cluster and inter-cluster interferences. While the former is the interference experienced by the $i_k$ UE from all BSs inside the $i$-th cluster, i.e.,

$$\mathbf{f}_{i_k,f_n} = \sum_{m=1}^{M} \sum_{j=1}^{|Q_i|} \sum_{n=1}^{F} \text{Tr}(\mathbf{H}_{i_k,i_j}^H\mathbf{H}_{i_k,i_j}^{-1} \psi_{m,i_j} u_{i_k,n}^H \mathbf{H}_{i_k,i_j}^{-1} \psi_{m,i_j}^Hv_{m,i_j}),$$

the latter is the received interference from all the BSs outside...
the $i$-th cluster and can be represented as

$$f_{i,k,f,n} = \sum_{q=1}^{M} \sum_{\ell=1}^{\|Q\|} \sum_{j=1}^{\|Q_j\|} C_{i,q}(f_n,i_j) \beta_{i,q,j} \times \text{Tr}(v_{i,q,j}^H H_{i,k,j}^H u_i u_{i,k} H_{i,k,j} v_{i,q,j}).$$

Therefore, the expected SINR at the $k$-th user in the $i$-th cluster, when user $i_k$ requests file $f_n$, can be written as Eqn. ($\overline{5}$), where $C_{i,q}(f_n,i_j) = C_{i,q}(f_n,q_j) D_{i,q}(q_j,q_k)$. Therefore the average transmission rate over channel realizations for user $i_k$, when it requests file $f_n$, is a function of transmit power, cache placement matrix, user association matrix, probability of file being requested, and distance from all connected BSs to $i_k$ user. Therefore, the total average throughput of the $i_k$ user can be formulated as

$$R_{i_k} = \mathbb{E}[R_{i_k,f,n}] = \sum_{n=1}^{P} \sum_{q=1}^{M} \sum_{\ell=1}^{\|Q\|} \sum_{j=1}^{\|Q_j\|} \beta_{i,q,j} \times \text{Tr}(v_{i,q,j}^H H_{i,k,j}^H u_i u_{i,k} H_{i,k,j} v_{i,q,j}).$$

where expectation is with respect to the random user requests. The distribution of the UEs' content demands follows a Zipf-like distribution $P_F(i)$ given as $P_F(i) = 1/i^\gamma$, $i \in \mathcal{F}$, where $\gamma$ models the skewness of the popularity profile ($\overline{10}$). Depending on both the BSs deployment strategies and the users' behavior, $\gamma$ can take different values. The popularity is uniformly distributed over content files for lower values of $\gamma$, meaning that users have more distinct interests. As $\gamma$ grows, the popularity becomes more skewed towards the most popular files, which means users have very similar file interests and a small subset of files are more desired than the rest.

III. PROBLEM FORMULATION AND ANALYSIS

In this section, the problem of interest is a joint optimization of the content placement and content delivery (precoding and user association). We formulate a mixed-timescale optimization problem which maximizes the trade off between the backhaul savings and the network throughput. For maximizing the backhaul reduction, each UE should be associated with a BS (cluster of BSs) that caches the largest amount of its desired contents. However, such a BS might be a long way away. On the other hand, in order to maximize the network throughput, each UE should take the BSs' load into account and accordingly associate with a BS that provides it a reasonably high SINR. Nonetheless, such a BS may not store the user's desired contents. Considering such a tradeoff into account, in this paper the problem of maximizing the user throughput and backhaul savings with respect to the precoding matrix, cache placement matrix, and user association matrix, is formulated subject to peak transmission power, cache capacity, and backhaul capacity constraints.

Let $\mathcal{V} = \{v_{i_k,i_j} \mid \Pi_{i}, \{H_{i_k,i_j}\}_{j=1}^{\|Q\|} \} : \forall i, k, j \}$ and $\mathcal{D} = \{D_{i} \mid \Pi_{i}, \{H_{i_k,i_j}\}_{j=1}^{\|Q\|} \} : \forall i, k, j \}$ denote all the beamforming vectors and user-association matrices for all user request profiles $\{\Pi_{i}\}_{i=1}^{M}$ and instantaneous channel state information matrices $\{H_{i_k,i_j}\}_{j=1}^{\|Q\|}$, respectively. Then for a given set of optimization variables $(\mathcal{V}, \mathcal{D}, \mathcal{C})$ and user request profiles $\{\Pi_{i}\}_{i=1}^{M}$, the average utility function of our optimization problem can be expressed as $\sum_{i=1}^{M} \sum_{\|I\|} \mathbb{E}[\lambda R_{i_k,f_n} + (1 - \lambda) \sum_{j=1}^{\|Q\|} \sum_{i \in K_{i,j}} (d_{i,k,j} C_{i,k}(f_n,i_j) \Pi_{i,j})]$ where the expectation is taken with respect to both the channel state information and the distribution of user requests, and the parameter controlling the tradeoff between network throughput and backhaul savings is denoted by $0 < \lambda < 1$ so that by adjusting $\lambda$ we can emphasize one term over the other. The optimization variables are partitioned into short-term (user association and beamforming) and long-term (content placement) variables. While the latter is adaptive to the popularity of data and the channel statistics, the former is adaptive to the instantaneous channel state information. The following feasible sets are defined for the cache placement $C_{i}$, the user association $D_{i}$, and the beamforming vectors $v_{i_k,i_j}$ for all $i \in \mathcal{M}, j \in \mathcal{Q}$, as follows

$$S_{C} = \{C_{i} : C_{i}(f_n,i_j) \in \{0,1\}, \sum_{n=1}^{P} C_{i}(f_n,i_j) \ell_{f_n} \leq s_{i_k}\}$$

$$S_{D} = \{D_{i} : D_{i}(i, i_j) \in \{0,1\}\}$$

$$S_{v} = \{v_{i_k,i_j} : \sum_{k=1}^{\|I\|} \text{Tr}(v_{i_k,i_j}^H H_{i_k,i_j}^H u_i u_{i_k} H_{i_k,i_j} v_{i_k,i_j}) \leq F_{i_k}^{\text{max}}\}$$

Then the joint content placement and content delivery problem $\mathcal{P}$ is formulated as follows\footnote{Note that we are considering a particular realization of the PPP, i.e., $B$ is a sample of a Poisson random variable.}:

maximize $\mathcal{C} \cup D \cup \mathcal{V}$

$$\sum_{i=1}^{M} \sum_{\|I\|} \mathbb{E}[\lambda R_{i_k,f_n} + (1 - \lambda) \sum_{j=1}^{\|Q\|} \sum_{i \in K_{i,j}} d_{i,k,j} C_{i,k}(f_n,i_j) \Pi_{i,j}]$$

subject to $C_{i} \in S_{C}$, $v_{i_k,i_j} \in S_{v}$, $D_{i} \in S_{D}$

$$\sum_{i_k \in K_{i,j}} d_{i,k,j} R_{i,k} \leq B_{i_j}, \forall i \in \mathcal{M}, j \in \mathcal{Q}_i$$

where $\sum_{i_k \in K_{i,j}} d_{i,k,j} R_{i,k}$ denotes the $i_j$ BS's backhaul consumption. The objective function can be expressed in a more compact form as $\sum_{i} \mathbb{E}[\text{Tr}(\lambda \mathcal{E}_i (\mathcal{P}_i \circ R_i) + (1 - \lambda) \mathcal{F}_i, C_i, D_i)]$ in which $\mathcal{E}_i$ is a $F \times \|I\|$ matrix full of 1’s, $R_i$ is a $\|I\| \times F$ rate matrix so that its $(i_k - f_n)$-th element is equal to $R_{i_k,f_n}$, and the expectation is taken with respect to the distribution of user requests.

Due to the coupled interference among mobile stations and the limited-backhaul capacity constraint, the optimization problem (7) is nonconvex. Moreover, the entries of user
association and cache placement matrices take binary values 0 and 1, thus the optimization problem falls into a mixed integer nonlinear programming (MINLP) which is usually NP-hard in general and non-tractable in practice. Since it is highly unlikely to compute a globally optimal solution in polynomial time, our goal is to obtain a tractable near-optimal solution by developing effective suboptimal algorithms. By utilizing the timescale separations of the optimization variables and making use of the fact that all constraints are separable, we divide the original optimization problem into three subproblems and propose an iterative algorithm that at each time maximizes the objective function with respect to one variable while assuming the other two variables are given. Therefore, each of these subproblems can be relaxed to a convex problem so that it can be solved efficiently. The mixed-timescale joint optimization of content delivery and content placement can be decomposed to the following subproblems:

(a) **Short-term Content Delivery**: As mentioned before, the content placement usually takes much longer than the content delivery. Therefore, in this subsection, it is assumed that the user request and the content placement matrix \( C_i \) is fixed and given. Therefore, we pay attention to the joint optimization of beamforming design and user-association (with respect to the user request). We further decouple the joint optimization problem in two stages. At the first stage, we associated each user with a cluster of BSs and at the second stage, assuming the user-association is fixed and given, we design the beamformers. The proposed algorithm is described as follows:

\[
P_1 : \text{maximize} \sum_{i=1}^{M} \sum_{j=1}^{\left| Q_i \right|} \sum_{k=1}^{\left| I_i \right|} d_{i,j,k} \mu_{i,j,k} \]
\[
\text{subject to} \quad d_{i,j,k} \left(1 - d_{i,j,k}\right) = 0, \forall i \in M, j \in Q_i, k \in I_i \]
\[
\mu_{i,j,k} \in \mathbb{R}^+, \forall i \in M, j \in Q_i, k \in I_i
\]

where \( \mu_{i,j,k} = \sum_{n=1}^{F} \tilde{p}_{i,n,j} C_i \) represents the amount of backhaul savings by associating the \( i \)-th UE with the \( j \)-th BS. Due to the fact that the entries of \( D_i \) take binary values 0 and 1, the optimization problem is mixed integer optimization over the user association. In order to solve this optimization problem and inspired by the idea used in [17], the main idea behind this method is to answer how the optimal value can be deduced from the constraints. This method is used in [17] and [25] to find a solution to the user association problem in heterogeneous cellular networks under the proportional fairness criterion. Using this method, the optimization problem can be easily decoupled among the clusters and the solution can be expressed as:

\[
d^*_{i,j,k} = \begin{cases} 1, & \text{if } \mu_{i,j,k} > 0 \\ 0, & \text{Otherwise} \end{cases}
\]

which shows that taking caching placement and thus backhaul reduction into account can be viewed as an additional incentive for UEs to associate with a BS.

**Beamforming Stage**: With fixed user association and request, the problem of designing beamforming vectors \( \mathbf{v}_{ik} \) and \( \mathbf{H}_{ik} \), \( i \in M, j \in Q_i \), can be written as

\[
P_2 : \text{maximize} \sum_{i=1}^{M} \sum_{k=1}^{\left| I_i \right|} \sum_{j=1}^{\left| Q_i \right|} \log(1 + \text{SINR}_{ik,f_n})
\]
\[
\text{subject to} \quad \tilde{p}_{ik,j} \mathbf{v}_{ik,j} \mathbf{v}_{ik,j}^H \mathbf{H}_{ik,j} \mathbf{v}_{ik,j}^H + \sigma_{ik} \mathbf{I} \mathbf{u}_{ik,j}
\]

where the optimal short-term beamformers will be calculated with respect to the given user request and thus, they do not depend on the file request probability. In order to suit our system model we applied the weighted minimum mean-square error (WMMSE) framework [31] into the above optimization problem and modified Proposition 3.2. in [32]. This way, each user can connect to a cluster of BSs instead of being served by only one BS. Thereby, problem \( P_2 \) can be effectively rewritten as

\[
\text{maximize} \sum_{i=1}^{M} \sum_{k=1}^{\left| I_i \right|} \sum_{j=1}^{\left| Q_i \right|} \log(1 + \text{SINR}_{ik,f_n})
\]
\[
\text{subject to} \quad \tilde{p}_{ik,j} \mathbf{v}_{ik,j} \mathbf{v}_{ik,j}^H \mathbf{H}_{ik,j} \mathbf{v}_{ik,j}^H + \sigma_{ik} \mathbf{I} \mathbf{u}_{ik,j}
\]

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\[
\text{maximize} \sum_{i=1}^{M} \sum_{k=1}^{\left| I_i \right|} \sum_{j=1}^{\left| Q_i \right|} \log(1 + \text{SINR}_{ik,f_n})
\]
\[
\text{subject to} \quad \tilde{p}_{ik,j} \mathbf{v}_{ik,j} \mathbf{v}_{ik,j}^H \mathbf{H}_{ik,j} \mathbf{v}_{ik,j}^H + \sigma_{ik} \mathbf{I} \mathbf{u}_{ik,j}
\]

where \( \{w_{ik}\} \) are the weights variable introduced by WMMSE framework and \( \{\varepsilon_{ik}\} \) are the mean square estimation errors which are defined by

\[

\varepsilon_{ik} = \frac{1}{2} - \sum_{j=1}^{\left| Q_i \right|} C_{ik}(f_n,j) \tilde{p}_{ik,j} \beta_{ik,j} \mathbf{u}_{ik,j}^H \mathbf{H}_{ik,j} \mathbf{v}_{ik,j} \mathbf{v}_{ik,j}^H + \sigma_{ik} \mathbf{I} \mathbf{u}_{ik,j}
\]

where \( \tilde{p}_{ik,j}, \beta_{ik,j} \) and \( \mathbf{H}_{ik,j} \) are the iteratively updated weights with a small positive regularization factor and the achievable data rate calculated from the previous iteration as in [33], respectively.

The objective function of (11) is convex with respect to each of the optimization variables \( \mathbf{v}_{ik,j}, \mathbf{u}_{ik,j} \), and \( w_{ik} \), which enables us to employ the block coordinate descent method to solve it [31]. To be specific, we maximize the cost function of
by updating one of three variables $v_{i,k,i,j}$, $u_{i,k,i,j}$, and $w_{i,k}$, while assuming the rest are given. In particular, we iteratively run the following steps.

- Initializing all the transmit beamformers $v_{i,k,i,j}$, $s$, $v_{i,k,i,j}$, and minimizing the weighted sum-MSE leads us to the MMSE receiver $u_{i,k}$ as follows

$$u_{i,k}^{m,n} = J_{i,k}^{-1} H_{i,k,i,j} v_{i,k,i,j}$$

where

$$J_{i,k} = \sum_{q=1}^{M} \sum_{\ell=1}^{T_q} \sum_{j=1}^{Q_{i,j}} C_{q,j}(f_{n,j}, q_{j}) \hat{P}_{q,j} \beta_{q,j,e} H_{i,k,i,j} v_{i,k,i,j}^H \sum_{\ell=1}^{T_q} H_{i,k,i,j} + \sigma_i^2 I$$

is the covariance matrix of the total received signal at the $i$th receiver.

- By fixing all $u_{i,k}$’s and $v_{i,k,i,j}$’s, $s$, $v_{i,k,i,j}$, the weights for all $i$ and $k$, can be updated as follows

$$w_{i,k} = (1 - \sum_{j=1}^{Q_{i,k}} C_{i,k}(f_{n,j}, q_{j}) \hat{P}_{q,j} \beta_{q,j,e} H_{i,k,i,j} v_{i,k,i,j}^H H_{i,k,i,j} v_{i,k,i,j})^{-1},$$

- By fixing all $w_{i,k}$’s and $u_{i,k}$’s, the transmit beamformers can be calculated using the following optimization problem

$$\begin{align*}
\text{minimize } & \sum_{i=1}^{M} \sum_{n=1}^{T_n} w_{i,k} x_{i,k}^2 \\
\text{subject to } & \sum_{k=1}^{T_n} \hat{p}_{i,k,j} \|v_{i,k,i,j}\|^2 \leq P_{j,i}, \\
& \sum_{k=1}^{T_n} d_{i,k,i,j} \hat{R}_{i,k,j} \|v_{i,k,i,j}\|^2 \leq B_{j,i}.
\end{align*}$$

Problem (14) is convex and (12) and (13) can be locally implemented at the users. Therefore, we solve problem (14) in a distributed manner based on the alternating direction method of multipliers (ADMM) [34]. In what follows, it is shown that by exchanging a fair amount of information between UEs and BSs the ADMM can be applied in a distributed fashion to solve optimization problem (14). In order to achieve a distributed implementation of the ADMM in the aforementioned cache-enabled C-RAN network, the following assumptions are made (similar to [31] and [23]). We assume that each BS $j \in Q_i$ knows $H_{i,k,i,j}$ for all $k$ user in cluster $B_{i,k}$ and each user $k$ can estimate the interference plus noise covariance matrix. Under these assumptions, the ADMM can be applied distributively. Note that, in order to identify the beamforming vectors in a distributed fashion, our aim here is to have a same form as the one in [34]. To do so, we introduce auxiliary variables $\{x_{i,k,i,j}\}$ and $\{X_{i,k,i,j}\}$ and rewrite problem (14) as

$$\begin{align*}
\text{minimize } & OB \\
\text{subject to } & \sum_{k=1}^{T_n} \hat{p}_{i,k,j} \|x_{i,k,i,j}\|^2 \leq P_{j,i}, \\
& \sum_{k=1}^{T_n} d_{i,k,i,j} \hat{R}_{i,k,j} \|x_{i,k,i,j}\|^2 \leq B_{j,i}.
\end{align*}$$

for all $i \in M$, $j \in Q_i$, $k \in I_i$, $m \in I_i$, $m \neq k$, $q \in M$, $q \neq i$, $\ell \in Q_q$, $m \in Q_q$, where the objective function

$$OB = \sum_{i=1}^{M} \sum_{n=1}^{T_n} \left( \sum_{j=1}^{Q_{i,j}} |\hat{v}_{i,k,j}^2 - \sum_{j=1}^{Q_{i,j}} \beta_{q,j,e} X_{i,k,i,j}^2 |^2 \right)$$

Then, we form the augmented Lagrangian as follows

$$L_P(\nu, x, X; \lambda_{i,k}, z_{i,k}) =$$

$$\begin{align*}
& \sum_{i=1}^{M} \sum_{n=1}^{T_n} \left( \sum_{j=1}^{Q_{i,j}} |\hat{v}_{i,k,j}^2 - \sum_{j=1}^{Q_{i,j}} \beta_{q,j,e} X_{i,k,i,j}^2 |^2 \right) \\
& + \sum_{n=1}^{T_n} \sum_{(i,j) \neq (k,j)} \sum_{j=1}^{Q_{i,j}} |\hat{v}_{i,k,j}^2 - \sum_{j=1}^{Q_{i,j}} \beta_{q,j,e} X_{i,k,i,j}^2 |^2 \\
& + \Re \left( \sum_{i=1}^{M} \sum_{n=1}^{T_n} \sum_{j=1}^{Q_{i,j}} |\hat{v}_{i,k,j}^2 - \sum_{j=1}^{Q_{i,j}} \beta_{q,j,e} X_{i,k,i,j}^2 |^2 \right)
\end{align*}$$

Then we can decompose the objective function as

$$L_P(\nu, x, X; \lambda_{i,k}, z_{i,k}) =$$

$$\begin{align*}
& \sum_{i=1}^{M} \sum_{n=1}^{T_n} \left( \sum_{j=1}^{Q_{i,j}} |\hat{v}_{i,k,j}^2 - \sum_{j=1}^{Q_{i,j}} \beta_{q,j,e} X_{i,k,i,j}^2 |^2 \right) \\
& + \sum_{n=1}^{T_n} \sum_{(i,j) \neq (k,j)} \sum_{j=1}^{Q_{i,j}} |\hat{v}_{i,k,j}^2 - \sum_{j=1}^{Q_{i,j}} \beta_{q,j,e} X_{i,k,i,j}^2 |^2 \\
& + \Re \left( \sum_{i=1}^{M} \sum_{n=1}^{T_n} \sum_{j=1}^{Q_{i,j}} |\hat{v}_{i,k,j}^2 - \sum_{j=1}^{Q_{i,j}} \beta_{q,j,e} X_{i,k,i,j}^2 |^2 \right)
\end{align*}$$

where $\rho$ is the penalty parameter, and $\lambda_{i,k} = \{\lambda_{i,k,m}|m,k \in I_i, j \in Q_i\}$ and $z_{i,k} = \{z_{i,k,m}|m,k \in I_i, j \in Q_i\}$ are the scaled dual variables for the last three sets of equality constraints.
Assuming \( \mathbf{v} \) is given, the constrained optimization problem with respect to \( \{\mathbf{x}, \mathbf{X}\} \) can be expressed as

\[
\min_{\mathbf{x}, \mathbf{X}} \mathcal{L}_p(\mathbf{v}, \mathbf{x}, \mathbf{X}; \lambda_{ik}, \mathbf{z}_{ik}),
\]

(19)

subject to \( \sum_{k=1}^{\left|\mathcal{I}\right|} \tilde{p}_{ik}, j \mathbf{x}_{ik}, j \leq P_{ij}, \quad \forall i \in \mathcal{M}, j \in \mathcal{Q}_i \)

\[
\sum_{ik \in \mathcal{K}_{ij}} d_{ij, ik} \tilde{R}_{ik} \| \mathbf{v}_{ik, ij} \|^2 \leq P_{ij}, \quad \forall i \in \mathcal{M}, j \in \mathcal{Q}_i
\]

which can be decomposed into \( i = 1, \ldots, M, \ k = 1, \ldots, |\mathcal{I}| \)

\[
\min_{\mathbf{X}_{ik}} \ g(X_{ik})
\]

(20)

where \( g(X_{ik}) \) is defined as

\[
g(X_{ik}) = -\sum_{m=1}^{\left|\mathcal{I}\right|} \sum_{m \neq k}^{\left|\mathcal{I}\right|} X_{im}^T \lambda_{im} X_{im} - \sum_{n=1}^{F} \tilde{p}_{ik}, f_n \left( \sqrt{\mathbf{w}}_{in} - \sum_{j=1}^{\left|\mathcal{Q}_i\right|} \tilde{p}_{ik}, f_n, C_i(f_n, ij) \tilde{p}_{ik}, ij \beta_{ik, ij} X_{ik}^T \right)^2
\]

\[
+ \frac{F}{2} \sum_{m=1}^{\left|\mathcal{I}\right|} \sum_{j=1}^{\left|\mathcal{Q}_i\right|} \| \mathbf{w}_{im} H_{im, ij} \mathbf{v}_{ik, ij} - X_{im} \|^2,
\]

and \( i = 1, \ldots, M \)

\[
\min_{\mathbf{X}_{ik}} \ h(X_{ik})
\]

subject to \( \sum_{k=1}^{\left|\mathcal{I}\right|} \| \mathbf{x}_{ik}, j \|^2 \leq P_{ij}, \quad \sum_{ik \in \mathcal{K}_{ij}} d_{ij, ik} \tilde{R}_{ik} \| \mathbf{v}_{ik, ij} \|^2 \leq P_{ij}, \quad \forall i \in \mathcal{M}, j \in \mathcal{Q}_i
\]

where \( h(X_{ik}) \) is defined as follows

\[
h(X_{ik}) \triangleq \Re \left( \sum_{k=1}^{\left|\mathcal{I}\right|} \sum_{j=1}^{\left|\mathcal{Q}_i\right|} \langle \mathbf{v}_{ik, ij} - \mathbf{x}_{ik}, j, \mathbf{z}_{ik}, j \rangle \right)
\]

\[
+ \frac{F}{2} \sum_{k=1}^{\left|\mathcal{I}\right|} \sum_{j=1}^{\left|\mathcal{Q}_i\right|} \| \mathbf{v}_{ik, ij} - \mathbf{x}_{ik}, j \|^2
\]

Note that all the three subproblems (18) and (20)–(21) are convex problems and can be solved efficiently. After calculating each variable at the \( m + 1 \) iteration, we will update the \( \lambda_{ik} \) as discussed earlier.

(b) Long-term Caching Placement:

As discussed earlier, the caching problem can be decoupled among all the clusters in the aforementioned cache-enabled Cloud-RAN network. Specifically, the caching problem for the \( i \)-th cluster can be expressed as the stochastic optimization problem (22) (since the average rate is in the form of expectation over all possible channel realizations and user requests), where \( \mu_{ij, f_n} = \sum_{k=1}^{\left|\mathcal{I}\right|} \tilde{p}_{ik}, f_n d_{ij, ik} \) represents the amount of backhaul saving due to storing \( f_n \)-th file in the \( i \)-th BS’s cache. Maximization of \( \sum_{n=1}^{F} \mu_{ij, f_n} C_i(f_n, ij) \) for a simple SISO case in which both BSs and UEs are equipped with a single antenna, and each UE is only connected with one BS is considered in (23). This maximization poses the following question: which files should be cached in the \( i \)-th BS to achieve the backhaul reduction \( \mu_{ij, f_n} \). Under the condition that all files have the same size, the optimal solution to maximize \( \sum_{n=1}^{F} \mu_{ij, f_n} C_i(f_n, ij) \) is caching the \( s_{ij} \) files that make the largest backhaul reduction; i.e.,

\[
C_i^*(f_n, ij) = \begin{cases} 1, & \text{if } \mu_{ij, f_n} \in \{\mu_{ij, f_1}, \ldots, \mu_{ij, f_{s_{ij}}}\} \\ 0, & \text{otherwise} \end{cases}
\]

where \( s_{ij} \) is the \( s \)-th item which is more requested in the list of \( \mu_{ij, f_n} \) (24). If each content has different sizes, the aforementioned caching strategy at each BS becomes a knapsack problem that can be solved using dynamic programming. Here, we consider a more general case than the one discussed in (23), by considering the multi-cluster multi-user MIMO network in which each UE can be associated with a cluster of BSs. Consequently, the optimization problem becomes more complicated and the objective function can be written as:

\[
O(C_i, C_{-i}) = \sum_{i=1}^{M} O_i(C_i, C_{-i})
\]

where \( C_{-i} \) is defined as follows

\[
C_{-i} = \{C_q \neq i \} \text{ and } M_i(C_i) \text{ defines as follows}
\]

\[
\sum_{j=1}^{\left|\mathcal{Q}_i\right|} \sum_{n=1}^{F} \tilde{p}_{ik}, f_n C_i(f_n, ij) d_{ij, ik} \tilde{p}_{ik}, ij \beta_{ik, ij} H_{ik, q_i} \mathbf{v}_{ik, ij} H_{ik, q_i}^H \mathbf{v}_{ik, ij} + \sigma^2 I
\]

and

\[
N_i(C_{-i}) = \sum_{(j,q) \neq (k,i)} \sum_{n=1}^{F} \tilde{p}_{ik}, f_n C_q(f_n, q_j) d_{ij, q_j} \tilde{p}_{ij}, q_j \beta_{ik, q_j} H_{ik, q_j} \mathbf{v}_{ik, q_j} H_{ik, q_j}^H \mathbf{v}_{ik, q_j} + \sigma^2 I
\]

Since the entries of \( C_i \) take binary values 0 and 1, the optimization problem falls into a mixed integer nonlinear programming category, which is usually NP-hard in general and non-tractable in practice. Therefore, we are interested in obtaining a near-optimal solution. We allow the binary variables to take real values in \([0, 1]\), and hence the original MINLP can be relaxed to a non-linear programming problem. Our aim is introducing a distributed solution method that efficiently computes the stationary solutions of this problem. To do so, we develop a stochastic parallel successive convex approximation (SCA)-based method (15) and substitute a series of strongly convex problems for the optimization problem (23). The main idea here is approximating the non-convex objective function \( O(C_i, C_{-i}) \) by a suitable convex approximation. To be specific, the aim of BSs in each cluster is to choose a feasible cache placement matrix \( C_i \) that maximizes the objective function \( O(C_i, C_{-i}) \) assuming the strategy profile \( C_{-i} \) is given. Our method is based on solving a sequence of parallel convex problems, one for each cluster. Each of these convex problems is obtained by maintaining the convex structure of the utility function while linearizing the rest around \( C_i \). To isolate the inter-cluster and intra-cluster interferences that make \( O(C_i, C_{-i}) \) nonconvex, we define the utility function of the clusters other than the \( i \)-th cluster as

\[
f_i(C_i, C_{-i}) = \sum_{s \neq i} \left( \lambda \sum_{k=1}^{\left|\mathcal{I}\right|} \sum_{n=1}^{F} \tilde{p}_{ik}, f_n \mathbb{E} \log_{2} \det \left( \mathbf{I} + M_a(C_s) \right) \right)
\]

\[
N_a^{-1}(C_{-s}) + \left(1 - \lambda\right) \sum_{n=1}^{F} \tilde{p}_{ik}, f_n C_s(f_n, s_j) \mathbb{E} \log_{2} \det \left( \mathbf{I} + M_a(C_s) \right)
\]

Making the objective function convex can be done by keeping the convex part; i.e., \( O_i(C_i, C_{-i}) \) while linearizing the nonconvex part; i.e., \( f_i(C_i, C_{-i}) \). As a consequence, we use the first order Taylor series expansion of the function
\[ \mathcal{P}_3: \maximize_{C_i} \left( \lambda \sum_{i=1}^{M} \sum_{k=1}^{\mathcal{I}_i} \sum_{n=1}^{F} \tilde{p}_{k,n} R_{n,k} f_n + (1 - \lambda) \sum_{i=1}^{M} \sum_{j=1}^{Q_i} \mu_{i,j} f_n C_i(f_n,i_j) \right) \]

subject to

\[ \sum_{n=1}^{F} C_i(f_n,i_j) \lambda f_n \leq s_{i_j}, \forall i \in \mathcal{M}, j \in Q_i \]

Recalling that \( \frac{d}{dx}(\log \gamma(\alpha)) = \gamma(\alpha)/\log \gamma(\alpha) \alpha \), the first-order differential is given by

\[ f'_i(C_i, C_{-i}) = \sum_{j \neq i} \left( \lambda \sum_{k=1}^{\mathcal{I}_i} \sum_{n=1}^{F} \frac{\tilde{p}_{k,n} f_n}{h(C_i)} \times \right. \]

\[ \left. - \sum_{j=1}^{Q_i} \frac{\tilde{p}_{k,n} f_n C_j(f_n,s_j) d_{s_j,i_j} \beta_{s_j,i_j} \tilde{p}_{s_j,i_j} \bar{v}_{s_j,i_j} \bar{e}_{s_j,i_j}}{h(C_i)} \right) \]

where \( \xi = \sum_{j=1}^{Q_i} \beta_{s_j,i_j} \lambda f_n d_{s_j,i_j} \tilde{p}_{s_j,i_j} \bar{v}_{s_j,i_j} \bar{e}_{s_j,i_j} \) and

\[ h(C_i) \] is given by (23).

By keeping only the linear term in the Taylor expansion of \( f'_i(C_i, C_{-i}) \) around \( C_i \) and adding a proximal like regularization term, the objective function in (22) can be approximated as

\[ \hat{O}(C_i, C_{-i}) = O_i(C_i, C_{-i}) + C_i(f_n,i_j) f'_i(C_i, C_{-i}) |_{c_i = C_i} - \frac{\tau_i}{2} C_i(f_n,i_j) - \hat{C}_i(f_n,i_j) \]

where \( \tau_i \) is a given nonnegative constant. Now, it is possible to approximate (22) by a set of \( |Q_i| \) per cluster problems given for \( i \in \mathcal{M} \) by

\[ \maximize_{C_i \in \mathcal{K}} \hat{O}(C_i, C_{-i}) \]

where \( \mathcal{K} \equiv \{ C_i(f_n,i_j) | \sum_{i=1}^{M} \sum_{j=1}^{Q_i} C_i(f_n,i_j) \lambda f_n \leq s_{i_j} \} \). Using the proposed algorithm in [36], for each BS we have the following best response mapping which consists of solving iteratively the sequence of (a strongly) convex optimization problem

\[ C_i(f_n,i_j) = \arg \max_{C_i \in \mathcal{K}} \hat{O}(C_i, C_{-i}) \]

Unlike (22), (25) is strongly convex and can be efficiently solved by numerical iterative algorithms.

**Remark 1:** (A Summary of Overall Operation) Utilizing the timescale separation of the optimization variables, we divide the original solution into short-term content delivery and long-term content placement. While the short-term process consists of user-association and beamforming optimization, the long-term process is composed of cache content placement. The content placement and the content delivery optimizations are performed in the cloud. The caching placement strategy is adaptive to the channel statistics. As soon as the user request profile changes, the cloud computes the updated cache placement and passes it to the BSs. Then the BSs update their cache. In each channel coherence time, the channel state information is acquired from the users through feedback, and the user-association and beamforming vectors are determined based on the instantaneous channel realization.

**Remark 2:** (Computational Complexity) Since we employ the WMMSE algorithm [31] for designing the beamformers, the computational complexity of the beamforming optimization problem is much like the WMMSE, with the difference being that the introduced ADMM-based algorithm decomposes the original large-scale problem into parallel small-scale subproblems. As a result, it needs more complex calculations than the coordinated descent method which is more desirable when the network size is small. However, the computation complexity of the introduced user-association algorithm is similar to [12] and is polynomial in relation to the network size. However, we further lower the complexity of associating a user with a BS by taking content placement into account and excluding the candidate users that increase the backhaul consumption from consideration. The computational complexity of the long-term caching placement is exceedingly low due to the fact that for each realization of the user request profile, the only thing the introduced algorithm needs to do is a simple Jacobi/Gauss-Seidel update.

**IV. SIMULATION EVALUATIONS**

In this preliminary simulation evaluation, we evaluate the performance of the proposed schemes in cache-enabled Cloud-RAN networks. The setup of our experiments is the following: we simulated a multi-cluster multi-user cache-enabled Cloud-RAN network in which the locations of the BSs are modeled using a PPP with density \( \lambda_B = 1/\pi R_B^2 \) = 5 BS/km, which corresponds to an average inter-site distance of 500 m. Multiple users are randomly and uniformly distributed around each BS, excluding an inner circle of 35 meters, as illustrated in Figure 2. The interference is subject to interference from all neighboring base stations that do not serve the specific user. The transmit antenna power gain and the transmit power at each BS is set to 10 dB and 46 dBm, respectively. The noise variance at the mobile station is fixed to \(-174 \text{ dBm}\). System bandwidth is taken as 5 MHz. We consider a possible antenna configuration in a typical deployment scenario for LTE/LTE Advanced systems: 4 transmit and 2 receive antennas. The simulation is run for 1000 channel realizations where each channel is uncorrelated Rayleigh fading and each channel element is drawn i.i.d from a complex Gaussian distribution with zero mean and variance 1, i.e., \( \mathcal{CN}(0,1) \). The pathloss is generated using 3 GPP (TR 36.814) methodology; i.e.,

\[ PL(dB) = 148.1 + 37.6 \log_{10}(d), \]

where \( d \) is the distance in kilometers. The log-normal shadowing parameter is assumed to be 8 dB. The total number of files available in the cloud is considered as \( F = 20 \). For the sake of simplicity, it is assumed...
that all files have the same size of one while the caches of the BSs can be filled with the \( s = \{1, 2, 4, 8, 10\} \) bits of the most popular files. A Zipf-like distribution with parameter 0.56 is considered for the file popularity.

The influence of the weighted coefficient on the objective introduced function in (10) is demonstrated in Figure 3. The results can be interpreted as follows: when \( \lambda \) increases the backhaul savings plays a less critical role than the network throughput. Conversely, when \( \lambda \) approaches zero the backhaul reduction dominates the objective function. Figure 3 also investigates the influence of the cache size. It shows that the defined weighted objective function of the network with bigger cache size always performs better than the system in which the BSs have a smaller cache. The reason is the smaller the cache sizes, the smaller the portions of the contents can be cached. Therefore, the files must be fetched from the cloud, which increases the backhaul usage. Moreover, when the size of caches grows from 2 to 8, an increase of approximately 76.42% in the backhaul savings is observed. Furthermore, 84% additional increase is acquired when the cache sizes enlarge from 1 to 2. This shows that even a small size of cache at each BS causes a substantial decrease in the backhaul usage.

Figure 4 demonstrates the performance comparison between our scheme and some benchmarks [37]. A different metric, normalized network cost, is used for the comparison, which is defined as a weighted sum of the backhaul cost and the transmit power cost. As shown in Figure 4, compared to the full group sparse beamforming (F-GSBF) algorithm and the partial group sparse beamforming (P-GSBF) algorithm proposed in [37], which considered the caching matrix is given, our introduced algorithm can reduce the network cost, which can interpreted as follows. Taking caching placement into account can be viewed as an additional incentive for backhaul reduction.

The average network throughput versus the SNR and the number of UEs in the cache-enabled Cloud-RAN are plotted in Figures 5 and 6, respectively. In Figure 5 we assume that each BS has the same cache size of 4 and the network contains 10 UEs. The algorithm is initialized by choosing a randomly generated feasible point. Moreover, the termination criterion is satisfied when the absolute value of the network throughput error in two consecutive rounds becomes smaller than \( 10^{-2} \).

In Figure 6, we assumed that UEs have the same SNR, due to the fact that co-scheduled UEs usually have similar SNRs in multi-user MIMO operation. The average network throughput is plotted for two different SNR values. It is observed that the average sum rate gradually increases when the number of UEs becomes larger.

In addition, the average number of iterations versus the number of UEs is plotted in Figure 7. The average is taken over 1000 independent channel realizations. It is observed that the algorithm converges in several steps. Moreover, the average CPU time versus the total number of UEs is plotted in Figure 8. Our experiments were run using MATLAB R2016b on a 3.6 GHz Intel(R) Xeon(R) E51620 Processor Cores machine, equipped with 8 GB of memory. As can be expected, the average CPU time increases with the number of UEs.

V. CONCLUSION

In this paper we introduced a novel iterative algorithm to increase the network throughput and backhaul savings of a multi-cluster multi-user Cloud-RAN, by jointly optimizing the user association, caching placement, and beamforming design. The proposed algorithm utilizes the ADMM along with the stochastic SCA-based method and enables all base stations to update their optimization variables in parallel. Simulation results demonstrate that efficiently designing of the caching placement along with the user association and beamforming design greatly influence the backhaul savings and network throughput.
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