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Energy Efficient Clustering and Beamforming for Cloud Radio Access Networks

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Abstract Cloud radio access network (Cloud-RAN) is recognized as one of the key enabling techniques for 5G due to its advantages in flexibility. In addition, the greatly increased energy efficiency (EE, evaluated by bits/Hz/J) is listed as one main objective when designing 5G wireless network. In this paper, we concentrate on EE optimization through Cloud-RAN enabled flexible multicell cooperative transmission. A joint clustering and beamforming problem for EE optimization is formulated. Due to the combinatorial nature of the clustering process and the non-convexity of the energy efficient beamforming design, the problem is difficult to solve directly. Therefore, we propose a hierarchical iterative framework to solve the problem. The origin optimization problem is decoupled into two subproblems, i.e., energy efficient beamforming problem and energy efficient cluster forming problem. Coalition formation game theory and fractional programming are utilized to obtain the optimal network cluster partition and beamformers respectively. Simulation results demonstrate the superior performance of the proposed algorithms.

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1 Introduction

Network densification has been historically adopted for capacity improvement and it will be persist in the future to handle the increasingly growing wireless traffic [1]. However, the dense deployment of base station (BS) leads to great challenge for network management. Since wireless traffic fluctuates both spatially and temporally, there should be no fixed cell size and transmission mode to enable efficient network operation. These challenges necessitate novel techniques that can well handle more complex deployment and interference scenarios, and can efficiently adapt to the traffic fluctuations dynamically [2].

In this context, cloud radio access networks (Cloud-RAN) has garnered significant interest. As a new centralized paradigm based on network virtualization, Cloud-RAN is recognized as one of the key enabling techniques for 5G [3]. By pooling the BSs' computational resources in a central location, Cloud-RAN can be cost effective in coping with denser networks and holds great promise for significant capacity enhancement. As shown in Fig. 1, Cloud-RAN consists of three parts, i.e., the remote radio heads (RRHs) equipped with multiple antennas, the centralized base band unit (BBU) pool and the fronthaul links which connect the large number of RRHs to BBU pool.

Network densification leads to severe intercell interference (ICI). In order to fully reap the benefits brought by the dense deployment, flexible and cost-efficient techniques are needed. Multicell cooperative transmission (MCT) has been

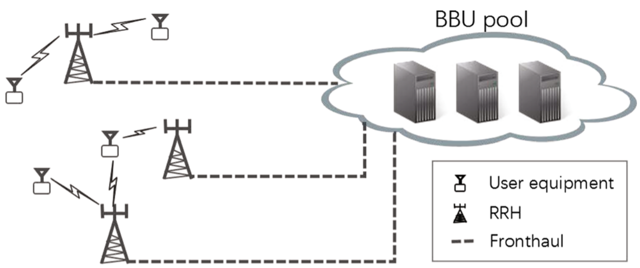

Fig. 1 Typical architecture of Cloud-RAN

recognized as an efficient solution for interference managements [4, 5]. The researches in [6] show that when all the BSs are coordinated, the spectral efficiency scales linearly with the signal-to-noise ratio (SNR). The basic idea of MCT is to let multiple BSs cooperate and act as a single Multiple Input Multiple Output (MIMO) transceiver, hence some of the interference are turned into useful signals [7]. Consequently, significantly network capacity gain can be achieved. MCT is also termed as coordinated/cooperative multi-cell MIMO, and can be seen as the evolution of MIMO techniques, which began from single user MIMO and evolved through multiuser MIMO to coordinated/cooperative multi-cell MIMO [8]. Owing to its centralized computing resources and high-speed interconnection among BSs, Cloud-RAN enables more flexible and dynamic MCT, which can be a very promising technique in coping with the complex interference scenario and can significantly improve the resource utilization [9].

On the other hand, network densification greatly increase the network energy consumption [10]. As the operators show greater interest in improving network energy efficiency (EE) to reduce operational expenditure (OPEX) and green house gas emissions, the research on EE has received extensive attention (see a survey in [11]). The greatly increased EE is also listed as one main objectives when designing 5G wireless network[12]. MCT also plays a vital role in EE optimization. In [9], virtual BS are dynamically formed according to the spatial traffic distribution in order to enable flexible MCT, through which network EE is greatly improved. In [13], an EE analysis framework for MCT is proposed and the results show that when the backhaul and cooperative processing power are carefully controlled, MCT can be very energy efficient, especially for cell-edge communication. Therefore, in order to fully reap the benefits of Cloud-RAN and MCT on EE enhancement, the joint optimization of RRHs clustering, and transmit beamforming is of enormous importance.

How to form clusters with desirable size is one foremost problem of energy efficient MCT design in Cloud-RAN. With the growing number of cooperating RRHs, the gains saturates due to the excessive overheads, e.g., complexity, signal processing and fronthaul power consumption [14]. Hence the number of cooperative cluster has to be carefully designed to obtain the optimal trade-off between the performance gain and associated overhead. In [15], a greedy clustering algorithm is proposed. Based on users' preference on serving BSs and the channel state information (CSI), the central unit can dynamically group BSs to maximize the network throughput. In [16], a novel affinity propagation model is used to semi-dynamically form the cooperative cluster, which can greatly improve network throughput with low complexity. Coalition formation game (CFG) studies the complex interactions among players and the formation of cooperating groups, termed as coalitions [17]. Hence, CFG is well suited for the BSs clustering problem and have been studied in [18, 19]. In [18], CFG is used to form the small cells cluster to optimize the tradeoff between the benefits and costs associated with cooperation. In [19], the authors utilize CFG theory to obtain the optimal cluster partition in Cloud-RAN. Based on stochastic geometry, the performance improvement brought by the cooperation is also analyzed. However, the above mentioned works only study the single-antenna BS case, and mainly focus on the throughput maximization problem. Energy efficient beamforming is another important problem for Cloud-RAN enabled MCT. The EE (defined as the sum throughput to power consumption) is in fractional form and hence fractional program is often used to solve the EE optimization problem. In [20], the downlink-uplink duality theory and geometric programming are used to find the beamformer that maximizes the network EE. In [21], weighted minimum mean square error (MMSE) based energy efficient beamforming strategy is proposed to maximize the worst-case EE. However, the research in [20] and [21] only focus on the beamforming problem for static and pre-determined cluster.

BS clustering and cooperation strategies are jointly designed in [22] to address the rate improvement and energy saving problem in heterogeneous networks, where BSs from different tiers form the cooperative clusters and jointly transmit the data stream to a typical user. Similar strategy is considered in [23], where authors aim to maximize users' normalized outage capacity. These works use tools from stochastic geometry to derive the optimal BS clustering and cooperation, and the clusters are formed merely based on the received signal strength. In [24] and [25], semi-dynamic clustering scheme and hybrid cooperative transmission mode are utilized to maximize the average net throughput, and the proposed cluster algorithm is merely based on the large-scale channel information to reduce the overhead. However, the cluster formation process in these works can't track the time varying wireless channels and bring BS cooperation into full play. As discussed in [26], dynamic clustering and beamforming design is an integer programming problem in nature. Hence benders decomposition method is used in [26] to find the optimal cooperation pattern and beamformers that lead to minimum power consumption. However, due to the high complexity of benders decomposition, the proposed algorithm is time-consuming. As an alternative, the authors in [27] use l_0-norm of the beamformer to indicate whether a certain BS is user's cooperating BS, and the mixed l_2/l_1 norm is adopt to approximate the origin l_0-norm. Based on the tools from group sparsity theory, the cluster partition and beamformers can be efficiently obtained. Similar strategies can be found in [28] and [29]. However, the mixed l_2/l_1 norm approximation is non-smooth and only suboptimal cluster partition can be obtained. Due to the combinatorial nature of the BS clustering and beamforming, two-stage solutions emerge as promising schemes. In [30], a greedy clustering algorithm is proposed to maximize the cooperation gain to guarantee cell edge users' performance, and then zero-forcing beamforming is adopt to further mitigate inter-cell interference. Similar scheme is proposed in [31] to maximize the network throughput. However, greedy method based clustering algorithms are of high complexity especially in large-scale networks. It can be noted that all the above mentioned works mainly focus on the throughput improvement or power consumption minimization. Actually, the EE optimization through joint clustering and beamforming design is a rather unexplored area. Existing works seldom dealt with the joint optimization of clustering and beamforming to maximize EE in the Cloud-RAN.

Differing from the existing works, in this paper, we address the dynamic clustering and beamforming problem for EE optimization in Cloud-RAN. The EE maximization problem through beamformer and cluster partition design is formulated. Due to the combinatorial nature of the RRHs clustering process and the non-convexity nature of the energy efficient beamforming design, the optimization problem is difficult to solve directly. Therefore in order to efficiently obtain the optimal solution, a hierarchical iterative framework is proposed, where the problem is decomposed into two coupled subproblems, i.e., the energy efficient cluster forming problem and the energy efficient bemforming problem. CFG based cluster forming algorithm is utilized to find the optimal network cluster partition. And to obtain the optimal beamformers, fractional program and MMSE model are exploited. The remainder of this article is organized as follows. We first introduce system model and formulate the optimization problem in Section 2. Then the energy efficient beamforming problem is efficiently solved in Section 3. In Section 4, we solve the energy efficient beamforming problem. The simulation results are presented in Section 5. Finally, we conclude the article in Section 6.

Regarding the notation, we use uppercase and lowercase bold face letters to denote matrices and vectors respectively. $(\cdot)^T$, $(\cdot)^H$ and $\mathbb{E}[\cdot]$ are transpose, Hermitian transpose and expectation operator. $\mathbf{I}$ represents identity matrix with appropriate dimension. $[x]^+$ denotes $\max\{0, x\}$.

2 System model and problem formulation

2.1 Signal model

We consider the downlink of a Cloud-RAN as shown in Fig. 2, where a set $\mathcal{Q}$ of RRHs, each equipped with M antennas, is serving a set $\mathcal{I}$ of user equipments (UEs) equipped with N antennas. Let $Q = (Q_1, \ldots, Q_k, \ldots, Q_K)$ which satisfies $\forall k_1, k_2 \in \{1, \ldots, K\}$, $Q_{k_1} \cap Q_{k_2} = \varnothing$, $\bigcup_{k=1}^{K} Q_k = \mathcal{Q}$ be a network partition, namely, a clustering decision. Q_k denotes the kth cooperative cluster, which serves a set I_k of users. Let $\mathbf{H}_{i_k}^{q_l} \in \mathbb{C}^{N\times M}$ denote the channel matrix from qth RRH in cluster l to the ith UE in the kth cluster. $\mathbf{H}_{i_k}^{l} \in \mathbb{C}^{N\times MQ_l}$ denotes the channel matrix from all RRHs in cluster l to UE i_k. Assume that RRHs in a cluster jointly transmit a single data stream to each served UE. Define $\mathbf{v}_{i_k}^{q_k} \in \mathbb{C}^{M\times 1}$ as the beamformer from BSs q_k to UE i_k and let $\mathbf{v}_{i_k} = \left[(\mathbf{v}_{i_k}^{1})^H, \ldots, (\mathbf{v}_{i_k}^{Q_k})^H\right]^H \in \mathbb{C}^{MQ_k\times 1}$ denote the beamformer collection intended for user i_k. Then the received signal $\mathbf{y}_{i_k} \in \mathbb{C}$ at i_kth UE can be expressed as

$$\mathbf{y}_{i_k} = \mathbf{H}_{i_k}^{k}\mathbf{v}_{i_k}s_{i_k} + \underbrace{\sum_{j_k\neq i_k}\mathbf{H}_{i_k}^{k}\mathbf{v}_{j_k}s_{j_k}}_{\text{Intra-cluster interference}} + \underbrace{\sum_{l\neq k}\sum_{j_l\in I_l}\mathbf{H}_{i_k}^{l}\mathbf{v}_{j_l}s_{j_l}}_{\text{Inter-cluster interference}} + \mathbf{z}_{i_k} \tag{1}$$

where $s_{i_k} \in \mathbb{C}$ is the normalized data symbol designated for i_kth UE and satisfies $\mathbb{E}\left[|s_{i_k}|^2\right] = 1$, $\mathbf{z}_{i_k}$ is the additive white

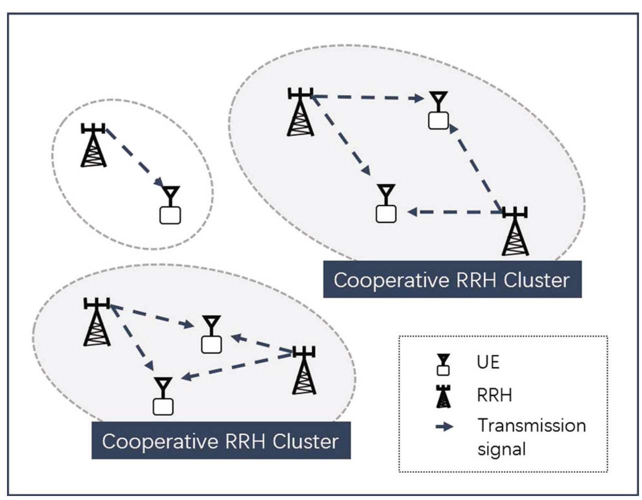

Fig. 2 System Model of cooperative Cloud-RAN

Gaussian noise (AWGN) vector subject to $\mathcal{CN}(0, \sigma_{i_k}^2 \mathbf{I}_N)$. Then the achievable rate at UE i_k can be expressed as

$$R_{i_k} = \log \Bigg| \mathbf{I}_N + \mathbf{H}_{i_k}^k \mathbf{v}_{i_k} \mathbf{v}_{i_k}^H \left(\mathbf{H}_{i_k}^k\right)^H \times \left(\sum_{(l,j)\neq(k,i)} \mathbf{H}_{i_k}^l \mathbf{v}_{j_l} \mathbf{v}_{j_l}^H \left(\mathbf{H}_{i_k}^l\right)^H + \sigma_{i_k}^2 \mathbf{I}_N \right)^{-1} \Bigg| \quad (2)$$

2.2 Power consumption model

The capacity gain brought by RRHs cooperation is accompanied with the increased power consumption due to the increased single processing and fronthaul transmission. In order to study the balance between performance gain and power consumption, we adopt the following power consumption model for the cooperative Cloud-RAN:

$$P_k = \xi P_k^{tx} + P_k^{sp} + P_k^{fh} + P_k^c \quad (3)$$

where P_k^{tx}, P_k^{sp}, P_k^{fh} and P_k^c denote the transmission power, the signal processing power consumption, fronthaul power consumption and the fixed power consumption for cooperative cluster k respectively, ξ is the reciprocal of power amplifier efficiency.

The transmit power radiated by kth cluster can be computed by

$$P_k^{tx} = \sum_{i_k \in I_k} \mathbf{v}_{i_k}^H \mathbf{v}_{i_k} \quad (4)$$

Cooperation introduces additional operation on each RRHs and connected BBUs. The joint signal processing is needed to suit cooperative transmission, which leads to extra power consumption at centralized BBUs pool. Hence we model the joint signal processing power consumption in kth cluster as

$$P_k^{sp} = p_k^{sp,c} + p_k^{sp}(|Q_k|) \quad (5)$$

where $p_k^{sp,c}$ denotes the fixed power cost that is independent of cluster size, and $p_k^{sp}(|Q_k|)$ is a cluster size related function. Here, according to [32], $p_k^{sp}(|Q_k|)$ is modeled to be a quadratic function of the cooperative cluster size, i.e., $p_k^{sp}(|Q_k|) = a_1 |Q_k| + a_2 |Q_k|^2$, where a_1 and a_2 are two constant parameters. Moreover, the transmitted signal should be delivered form BBUs to the RRHs in the cluster through the fronthaul. The caused power consumption is modeled as

$$P_k^{fh} = \frac{1}{C_{fh}} \left(\frac{2pq\,|Q_k|^2}{T_s} \right) \quad (6)$$

where C_{fh} denotes the fronthaul capacity and T_s denotes the symbol period. p and q represent the additional pilot density and relevant signaling, respectively.

2.3 Problem formulation

Network Energy efficiency is defined as $\mathrm{EE}(\{\mathbf{v}_{i_k}\}, Q) = \frac{\sum_{k=1}^K C_k(\{\mathbf{v}_{i_k}\}, Q)}{\sum_{k=1}^K P_k(\{\mathbf{v}_{i_k}\}, Q)}$, where $C_k(\{\mathbf{v}_{i_k}, Q\})$ denotes the throughput of kth cluster and is given by

$$C_k(\{\mathbf{v}_{i_k}\}, Q) = \sum_{i_k \in I_k} R_{i_k}(\{\mathbf{v}_{i_k}\}, Q) \quad (7)$$

Assume that each RRH has the maximum transmit power constraint when performs downlink transmission, which is molded as

$$P_{q_k}^{tx} = \sum_{i_k \in I_k} \mathbf{v}_{i_k}^H \Phi_{q_k} \mathbf{v}_{i_k} \le p_{q_k} \quad (8)$$

where Φ_{q_k} denotes the RRH selection matrix which has all zeros except M ones on the main diagonal corresponding to the M antennas of RRH q_k. Hence, the energy efficient clustering and beamforming problem for EE optimization can be formulated as

$$\begin{aligned} \mathbf{P1}: \quad & \underset{\{\mathbf{v}_{i_k}\}, Q}{\text{maximize}} \quad \mathrm{EE}(\{\mathbf{v}_{i_k}\}, Q) \\ & \text{subject to} \quad \textstyle\sum_{i_k \in I_k} \mathbf{v}_{i_k}^H \Phi_{q_k} \mathbf{v}_{i_k} \le p_{q_k}, \forall q_k \in \mathcal{Q} \end{aligned} \quad (9)$$

Due to the combinatorial nature of the RRHs clustering and the nonconvexity nature of the energy efficient beamforming design, the underlying optimization problem is NP-hard. To efficiently solve the non-convex combinatorial optimization problem **P1**, we adopt the hierarchical iterative scheme. **P1** is decomposed into two coupled subproblems, i.e., energy efficient clustering and energy efficient beamforming, which are defined as follows

$$\arg\max_{Q} \left\{ \max_{\{\mathbf{v}_{i_k}\}} \mathrm{EE}(\{\mathbf{v}_{i_k}\}, Q) \right\} \quad (10)$$

A framework utilizing hierarchical iterative scheme is proposed to solve the above problem. Our proposed framework contains two main "components" as shown in Fig. 3. In outer iteration, the energy efficient clustering component is

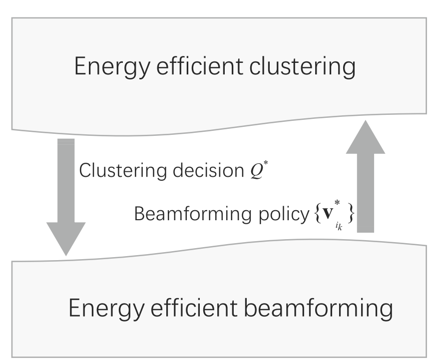

Fig. 3 Conceptual overview of the proposed framework

exploited to obtain the clusters partition $\mathcal{Q}$. In inner iteration, the energy efficient beamforming component is utilized to achieve the optimal beamformers given the cluster partition.

3 Energy efficient beamforming design

3.1 Problem transformation

In this section, we aim to solve the following energy efficient beamforming problem with cluster decision $\mathcal{Q}$ given,

$$\mathbf{P2}: \quad \underset{\{\mathbf{v}_{i_k}\}}{\text{maximize}} \quad \frac{\sum_{k=1}^{K} C_k(\{\mathbf{v}_{i_k}\})}{\sum_{k=1}^{K} P_k(\{\mathbf{v}_{i_k}\})}$$
$$\text{subject to} \quad \sum_{i_k \in \mathcal{I}_k} \mathbf{v}_{i_k}^H \Phi_{q_k} \mathbf{v}_{i_k} \le p_{q_k}, \forall q_k \in \mathcal{Q} \tag{11}$$

Problem **P2** is nonconvex due to nonconvexity of the data rate expression in Eq. 2. Hence in order to find the optimal solution, we transformed the origin problem into easily solvable one by introducing a lower bound of the $\mathrm{EE}(\{\mathbf{v}_{i_k}\})$.

Note that the data rate in Eq. 2 is achieved by a maximal likelihood detector at each UE, here we exploit the minimum mean square error (MMSE) detector [33]. Let $\mathbf{u}_{i_k} \in \mathbb{C}^{N\times 1}$ denote the receiver filter at i_kth UE to decode the intended signal and define the estimated signal as $\hat{s}_{i_k} = \mathbf{u}_{i_k}^H \mathbf{y}_{i_k}$. Then the mean square error (MSE) of UE i_k can be calculated as

$$\begin{aligned}\mathrm{MSE}_{i_k} &= \mathbb{E}_{s,\mathbf{z}}\left[(\hat{s}_{i_k} - s_{i_k})(\overline{\hat{s}_{i_k}} - \overline{s_{i_k}})\right] \\ &= (1 - \mathbf{u}_{i_k}^H \mathbf{H}_{i_k}^k \mathbf{v}_{i_k})(1 - \overline{\mathbf{u}_{i_k}^H \mathbf{H}_{i_k}^k \mathbf{v}_{i_k}}) \\ &\quad + \sum_{(l,j)\neq(k,i)} \mathbf{u}_{i_k}^H \mathbf{H}_{i_k}^l \mathbf{v}_{jl} \mathbf{v}_{jl}^H (\mathbf{H}_{i_k}^l)^H \mathbf{u}_{i_k} + \sigma_{i_k}^2 \mathbf{u}_{i_k}^H \mathbf{u}_{i_k}\end{aligned} \tag{12}$$

Referring to [33], define the lower bound of the data rate as

$$\tilde{R}_{i_k}(\{\mathbf{v}_{i_k}\}, \{\mathbf{u}_{i_k}\}, \{w_{i_k}\}) \triangleq \log w_{i_k} - w_{i_k}\mathrm{MSE}_{i_k} + 1 \tag{13}$$

where w_{i_k} is a positive weight for UE i_k.

Lemma 1 *$\tilde{R}_{i_k}(\{\boldsymbol{v}_{i_k}\}, \{\boldsymbol{u}_{i_k}\}, \{w_{i_k}\})$ is concave w.r.t. each group of the variables $\{\boldsymbol{v}_{i_k}\}$, $\{\boldsymbol{u}_{i_k}\}$, $\{w_{i_k}\}$ when others are fixed. Moreover, $\tilde{R}_{i_k}(\{\boldsymbol{v}_{i_k}\}, \{\boldsymbol{u}_{i_k}\}, \{w_{i_k}\})$ is a lower bound of the data rate R_{i_k} in* Eq. 2 *and the bound is tight at the optimal point $\{\boldsymbol{v}_{i_k}^*\}$, $\{\boldsymbol{u}_{i_k}^*\}$, $\{w_{i_k}^*\}$.*

Proof Due to the concavity of $\log(w_{i_k})$, the function is concave w.r.t. w_{i_k}. Moreover, according to the MSE expression in Eq. 12, it can be observed that $\tilde{R}_{i_k}(\{\mathbf{v}_{i_k}\}, \{\mathbf{u}_{i_k}\}, \{w_{i_k}\})$ is concave w.r.t. $\{\mathbf{v}_{i_k}\}$, $\{\mathbf{u}_{i_k}\}$, $\{w_{i_k}\}$ when others are fixed. Then we prove that R_{i_k} is the maximum of $\tilde{R}_{i_k}(\{\mathbf{v}_{i_k}\}, \{\mathbf{u}_{i_k}\}, \{w_{i_k}\})$. Define the MMSE at UE i_k as $\mathrm{MMSE}_{i_k} = \min_{\mathbf{u}_{i_k}} \mathrm{MSE}_{i_k}$. When the beamformers $\{\mathbf{v}_{i_k}\}$ are given, setting the gradient of the MSE function w.r.t. $\mathbf{u}_{i_k}$ to zero, we can find the expression of the MMSE receive filter for UE i_k as:

$$\begin{aligned}\mathbf{u}_{i_k}^* &= \left(\sum_{(l,j)} \mathbf{H}_{i_k}^l \mathbf{v}_{jl} \mathbf{v}_{jl}^H (\mathbf{H}_{i_k}^l)^H + \sigma_{i_k}^2 \mathbf{I}_N\right)^{-1} \mathbf{H}_{i_k}^k \mathbf{v}_{i_k} \\ &\triangleq \left(\mathbf{H}_{i_k}^k \mathbf{v}_{i_k} \mathbf{v}_{i_k}^H (\mathbf{H}_{i_k}^k)^H + \Sigma_{i_k}\right)^{-1} \mathbf{H}_{i_k}^k \mathbf{v}_{i_k}\end{aligned} \tag{14}$$

where Σ_{i_k} denotes effective noise covariance matrix at UE i_k:

$$\Sigma_{i_k} = \sum_{(l,j)\neq(k,i)} \mathbf{H}_{i_k}^l \mathbf{v}_{jl} \mathbf{v}_{jl}^H (\mathbf{H}_{i_k}^l)^H + \sigma_{i_k}^2 \mathbf{I}_N \tag{15}$$

Furthermore, by taking gradient of $\tilde{R}_{i_k}(\{\mathbf{v}_{i_k}\}, \{\mathbf{u}_{i_k}\}, \{w_{i_k}\})$ over w_{i_k}, and let $\partial \tilde{R}_{i_k}(\{\mathbf{v}_{i_k}\}, \{\mathbf{u}_{i_k}\}, \{w_{i_k}\})/\partial w_{i_k} = 0$, we can obtain the optimal weight for UE i_k as

$$w_{i_k}^* = \left(\mathrm{MSE}_{i_k}\right)^{-1} \tag{16}$$

Substituting Eq. 14 into Eq. 12, we can obtain

$$\mathrm{MMSE}_{i_k} = 1 - \mathbf{v}_{i_k}^H (\mathbf{H}_{i_k}^k)^H \left(\mathbf{H}_{i_k}^k \mathbf{v}_{i_k} \mathbf{v}_{i_k}^H (\mathbf{H}_{i_k}^k)^H + \Sigma_{i_k}\right)^{-1} \mathbf{H}_{i_k}^k \mathbf{v}_{i_k} \tag{17}$$

Then substituting Eqs. 16 and 17 into Eq. 13, we can obtain [33]

$$\begin{aligned}&\tilde{R}_{i_k}(\{\mathbf{v}_{i_k}\}, \{\mathbf{u}_{i_k}\}, \{w_{i_k}\}) \\ &= \log\left|\left(\mathrm{MMSE}_{i_k}\right)^{-1}\right| \\ &\overset{(a)}{=} \log\left|1 + \mathbf{v}_{i_k}^H (\mathbf{H}_{i_k}^k)^H \left(\Sigma_{i_k}\right)^{-1} \mathbf{H}_{i_k}^k \mathbf{v}_{i_k}\right| \\ &\overset{(b)}{=} \log\left|\mathbf{I}_N + \mathbf{H}_{i_k}^k \mathbf{v}_{i_k} \mathbf{v}_{i_k}^H (\mathbf{H}_{i_k}^k)^H \left(\Sigma_{i_k}\right)^{-1}\right|\end{aligned} \tag{18}$$

where equality (a) follows from applying the *Woodbury formula* to Eq. 17, equality (b) follows from the fact that $\det(\mathbf{I}+\mathbf{AB}) = \det(\mathbf{I}+\mathbf{BA})$. Comparing (18) and (2), we can conclude that $\tilde{R}_{i_k}(\{\mathbf{v}_{i_k}\}, \{\mathbf{u}_{i_k}\}, \{w_{i_k}\})$ is a lower bound of the data rate R_{i_k} in Eq. 2 and the bound is tight at the optimal point $\{\mathbf{v}_{i_k}^*\}$, $\{\mathbf{u}_{i_k}^*\}$, $\{w_{i_k}^*\}$. □

According to Lemma 1, we can also construct the following lower bound of the objective function in **P2**:

$$\begin{aligned}&\mathrm{EE}(\{\mathbf{v}_{i_k}\}, \{\mathbf{u}_{i_k}\}, \{w_{i_k}\}) \\ &= \frac{\sum_{k=1}^{K} \sum_{i_k \in I_k} \tilde{R}_{i_k}(\{\mathbf{v}_{i_k}\}, \{\mathbf{u}_{i_k}\}, \{w_{i_k}\})}{\sum_{k=1}^{K} P_k(\{\mathbf{v}_{i_k}\})}\end{aligned} \tag{19}$$

The bound is tight at the optimal point $\{\mathbf{v}_{i_k}^*\}$, $\{\mathbf{u}_{i_k}^*\}$, $\{w_{i_k}^*\}$. Note that after the above transformation, **P2** is still in fractional form. By applying fractional programming, we can establish the following proposition:

Proposition 1 *P2 has optimal objective value θ^* if and only if $f(\theta^*) = 0$, where univariate function $f : \mathbb{R} \longmapsto \mathbb{R}$ is defined as*

$$f(\theta) \triangleq \underset{\{\boldsymbol{v}_{i_k}\},\{\boldsymbol{u}_{i_k}\},\{w_{i_k}\}}{\text{maximize}} \sum_{k=1}^{K}\sum_{i_k\in I_k} \tilde{R}_{i_k}(\{\boldsymbol{v}_{i_k}\},\{\boldsymbol{u}_{i_k}\},\{w_{i_k}\}) - \theta \sum_{k=1}^{K} P_k(\{\boldsymbol{v}_{i_k}\})$$
$$\text{subject to} \quad \sum_{i_k\in I_k} \boldsymbol{v}_{i_k}^H \Phi_{q_k} \boldsymbol{v}_{i_k} \le p_{q_k}, \forall q_k \in \mathcal{Q} \tag{20}$$

Proof We can easily obtain the following property of the objective function of **P1**:

(1) The objective function is bounded. Note that the following relationship exists

$$0 \le \sum_{i_k\in I_k} \tilde{R}_{i_k}(\{\mathbf{v}_{i_k}\},\{\mathbf{u}_{i_k}\},\{w_{i_k}\}) \le C_k^{max} \tag{21a}$$

$$P_c \le P_k(\{\mathbf{v}_{i_k}\}) \le \sum_{q_k\in Q_k} \xi p_{q_k} + P_c \tag{21b}$$

where $C_k^{max} = \sum_{i_k\in I_k} \log \left|\mathbf{I}_N + \mathbf{H}_{i_k}^k \mathbf{v}_{i_k}\mathbf{v}_{i_k}^H (\mathbf{H}_{i_k}^k)^H\right|$ and P_c denotes the load-independent power consumption in cluster k. Therefore, we can also obtain the range of objective function as $0 \le \mathrm{EE}(\{\mathbf{v}_{i_k}\},\{\mathbf{u}_{i_k}\},\{w_{i_k}\}) \le C_k^{max}/P_c$.

(2) The numerator in Eq. 19 is concave w.r.t. $\{\mathbf{v}_{i_k}\}$ and the denominator is convex w.r.t. $\{\mathbf{v}_{i_k}\}$, then $\mathrm{EE}(\{\mathbf{v}_{i_k}\},\{\mathbf{u}_{i_k}\},\{w_{i_k}\})$ is quasi-concave w.r.t. $\{\mathbf{v}_{i_k}\}$ when $\{\mathbf{u}_{i_k}\},\{w_{i_k}\}$ are fixed.

Based on the obtained property and the derivations in [34] and [35], we can conclude that $f(\theta)$ is a monotonically decreasing function of θ and the equation $f(\theta) = 0$ has a unique solution θ^*. Therefore if we find certain θ that makes the objective function of Eq. 20 equals to zero, then the corresponding beamformers are also the optimal beamformers of problem **P2**. □

Similar to [33] and [36], we can establish the following proposition for the equivalence relationship between **P2** and Eq. 20.

Proposition 2 *If $(\{\boldsymbol{v}_{i_k}^*\},\{\boldsymbol{u}_{i_k}^*\},\{w_{i_k}^*\})$ is the optimal solution to **P2**, then $\{\boldsymbol{v}_{i_k}^*\}$ must be the optimal solution to* Eq. 20. *Conversely if $\{\boldsymbol{v}_{i_k}^*\}$ is the optimal solution of* Eq. 20, *then $(\{\boldsymbol{v}_{i_k}^*\},\{\boldsymbol{u}_{i_k}^*\},\{w_{i_k}^*\})$ must be the optimal solution to **P2**.*

3.2 Algorithm design

In what follows, we solve the problem in Eq. 20 for given θ, $\{\mathbf{u}_{i_k}\}$ and $\{w_{i_k}\}$. To express in a more compact way, we remove the constant terms and reformulate it as

$$\mathbf{P3}: \quad \underset{\{\mathbf{v}_{i_k}\}}{\text{minimize}} \quad \sum_{k=1}^{K}\sum_{i_k\in I_k} w_{i_k}\mathrm{MSE}_{i_k} + \theta\xi \sum_{k=1}^{K}\sum_{i_k\in I_k} \mathbf{v}_{i_k}^H\mathbf{v}_{i_k}$$
$$\text{subject to} \quad \sum_{i_k\in I_k} \mathbf{v}_{i_k}^H \Phi_{q_k}\mathbf{v}_{i_k} \le p_{q_k}, \forall q_k \in \mathcal{Q}$$
$$\mathrm{MSE}_{i_k} \text{ is given by (12).} \tag{22}$$

Since both the optimization objective and constraints are convex, strong duality holds and the Karush-Kuhn-Tucker (KKT) conditions are necessary and sufficient for the optimal solution. Hence we use Lagrangian duality theory to solve **P3**. Formally, the Lagrangian function can be stated as

$$\begin{aligned}\mathcal{L}(\{\mathbf{v}_{i_k}\},\{\lambda_{q_k}\}) = &\sum_{k=1}^{K}\sum_{i_k\in I_k} w_{i_k}\Bigg(1 + \sum_{(l,j)} \mathbf{u}_{i_k}^H \mathbf{H}_{i_k}^l \mathbf{v}_{jl}\mathbf{v}_{jl}^H (\mathbf{H}_{i_k}^l)^H \mathbf{u}_{i_k} \\ &- \mathbf{u}_{i_k}^H \mathbf{H}_{i_k}^k \mathbf{v}_{i_k} - \mathbf{v}_{i_k}^H (\mathbf{H}_{i_k}^k)^H \mathbf{u}_{i_k}\Bigg) \\ &+ \theta\xi \sum_{k=1}^{K}\sum_{i_k\in I_k} \mathbf{v}_{i_k}^H \mathbf{v}_{i_k} \\ &+ \sum_{q_k\in\mathcal{Q}} \lambda_{q_k}\left(\sum_{i_k\in I_k} \mathbf{v}_{i_k}^H \Phi_{q_k}\mathbf{v}_{i_k} - p_{q_k}\right)\end{aligned} \tag{23}$$

where $\{\lambda_{q_k}\}$ denote the Lagrange multipliers associated with the power constraints. The dual problem is given by

$$\max_{\{\lambda_{q_k}\}} \min_{\{\mathbf{v}_{i_k}\}} \mathcal{L}(\{\mathbf{v}_{i_k}\},\{\lambda_{q_k}\}) \tag{24}$$

Setting the gradient of Eq. 23 w.r.t. $\mathbf{v}_{i_k}$ to zero, we can obtain the optimal beamformer for UE i_k as:

$$\mathbf{v}_{i_k}^* = w_{i_k}\left(\sum_{(l,j)} w_{jl}(\mathbf{H}_{jl}^k)^H \mathbf{u}_{jl}\mathbf{u}_{jl}^H \mathbf{H}_{jl}^k + \theta\xi\mathbf{I} + \sum_{q_k\in Q_k} \lambda_{q_k}\Phi_{q_k}\right)^{-1} (\mathbf{H}_{i_k}^k)^H \mathbf{u}_{i_k} \tag{25}$$

To find the optimal $\{\lambda_{q_k}\}$, we use the gradient method and the update equation is given by

$$\lambda_{q_k}^{n+1} = \left[\lambda_{q_k}^n + s(n)\left(\sum_{i_k\in I_k} \mathbf{v}_{i_k}^H \Phi_{q_k}\mathbf{v}_{i_k} - p_{q_k}\right)\right]^+ \tag{26}$$

Based on the above derivation and the block coordinate ascent method, we develop Algorithm 1 to achieve the EE optimal beamformers.

Algorithm 1 Energy efficient beamforming algorithm

```
Initialize θ;
repeat
    Set t = 0, initialize {v^t_{i_k}};
    repeat
        Sequentially update u^t_{i_k}, w^t_{i_k} according to Eqs. 14 and 16;
        Set t = t + 1;
        Compute {λ_{q_k}} according to Eq. 26, then update v^{t+1}_{i_k} according to Eq. 25;
    until certain criteria met.
    update θ;
until θ converges.
```

4 Energy efficient clustering design

In this section, we focus on solving the energy efficient clustering problem, i.e., find a optimal network partition that maximizes EE. We first formulate an energy efficient clustering game and then propose an iterative algorithm to obtain the optimal cluster decision.

4.1 Energy efficient cluster forming game formulation

Coalition formation game (CFG) studies the complex interactions among players and the formation of cooperating groups [17]. Hence, CFG is well suited for the RRHs clustering problem in Cloud-RAN. We define the energy efficient cluster forming game (EECFG) as a triplet, $\mathbb{G}_{\text{EECF}} = (\mathcal{Q}, u, Q)$ in a characteristic form. $\mathcal{Q}$ denotes the set of players, namely RRHs. RRHs are affected each other through mutual interference, and they seek to form cooperative clusters to improve energy efficiency. Moreover, u is a characteristic function that quantifies the value of a coalition. As described in section 2, $Q = \{Q_1, \ldots, Q_k, \ldots, Q_K\}$ is a partition of $\mathcal{Q}$ and shows a cooperative structure of the network. Cluster value set is defined as

$$u(Q_k) = \{\upsilon(Q_k) \in \mathbb{R}^{|Q_k|} | \upsilon_{q_k}(Q_k), \forall q_k \in Q_k\} \tag{27}$$

where $\upsilon_{q_k}(Q_k)$ is an element of $\upsilon(Q_k)$ and represents the utility that RRH $q_k \in Q_k$ can obtain in the coalition Q_k. Here, we define the utility of RRH as the EE it achieves when serving attached users.

Remark 1 As discussed in the Section 3, the objective of the energy efficient clustering problem is to find a network partition that maximizes the network EE. However, this process is of high complexity and extremely hard to solve for large networks. Hence here, we define the value of a cluster as its achieved EE when serving attached users. Based on the CFG, only if each RRH in a cluster can enjoy EE gain, they cooperate. So the proposed energy efficient clustering game is a solution that considers fairness among RRHs and can obtain a suboptimal network partition with low complexity.

From the EECFG definition, we can easily obtain the following lemma:

Lemma 2 *Given the characteristic function in (16), the energy-efficient cluster forming game $\mathbb{G}_{EECF}$ has non-transferable utility (NTU).*

Proof The characteristic function u of $\mathbb{G}_{EECF}$ is such a mapping that for any cluster $Q_k \in \mathcal{Q}$, $u(Q_k)$ is a closed convex subset of $\mathbb{R}^{|Q_k|}$ which contains the utility vectors obtained by RRHs in Q_k. Moreover, note that the utility obtained by each RRH in Q_k is related to the joint strategies that all RRHs in Q_k select. Hence, the cluster utility value cannot be arbitrarily apportioned among the members. So the proposed $\mathbb{G}_{\text{EECF}}$ has a nontransferable utility (NTU). □

4.2 Algorithm design and property analysis

To obtain the optimal coalitional structure for the game $\mathbb{G}_{\text{EECF}}$, we adopt the efficient merge and split rules[37]. The basic idea is to enable RRHs to join or leave a coalition based on the predefined preferences so as to maximize the system utility. Here we adopt pareto order $\triangleright_p$ [17] as the preference order based on which RRHs can compare and order their potential coalitions. Let $h(\bar{Q})$ denote the history clustering information, and then the modified merge and split rule can be respectively defined as:

Definition 1 *Merge rule*: merge any two coalitions Q_{k_1}, Q_{k_2}, if $\begin{cases} \{Q_{k_1} \cup Q_{k_2}\} \triangleright_p \{Q_{k_1}, Q_{k_2}\} \\ \{Q_{k_1} \cup Q_{k_2}\} \notin h(\bar{Q}) \end{cases}$;

Definition 2 *Split rule*: split any coalitions $\{Q_{k_1}, Q_{k_2}\}$ into two coalitions Q_{k_1}, Q_{k_2},
if $\begin{cases} \{Q_{k_1}, Q_{k_2}\} \triangleright_p \{Q_{k_1} \cup Q_{k_2}\} \\ \{Q_{k_1}, Q_{k_2}\} \notin h(\bar{Q}) \end{cases}$.

Denote Q^* as the resulting partition of merge and split operations, then we can establish the following proposition.

Proposition 3 *For each cluster in the resulting partition Q^*, the members are mutually interfered RRHs.*

Proof Dense and irregularly deployment of RRHs leads to severe and dynamic ICI. A RRH may suffer from several dominating interfering RRHs. In order to improve its EE, a RRH is encouraged to cooperate with its interference neighborhood. However, when a RRH cooperates with RRH whose interference is negligible, the capacity gain is limited. Meanwhile additional power consumption of RRH will be produced, which results in the EE degradation. □

Hence in the proposed $\mathbb{G}_{\mathrm{EECF}}$, we assume that RRHs can only cooperate with its interference neighborhood to reduce complexity. In order to facilitate the merge and split operations, we introduce the concept of dominant interferer [38] for each cluster as follows.

Definition 3 *Dominant Interferer (DI)*: A cluster of aggressor RRHs, the interference of which dominates the total interference for a certain cluster. Based on the calculated interference I_l of cluster l, the DI for cluster Q_k can be mathematically described as $\mathrm{DI}_k = \arg\max_l I_l$

Based on the above analysis, we develop the CFG-based energy efficient clustering algorithm as follows. The network partition is first initialized to $Q^0 = \{\{1\}, \ldots, \{|\mathcal{Q}|\}\}$, i.e., each RRH separately serves its attached users. When the ICI is severe and EE performance is undesirable, RRHs have the incentive to cooperate with RRHs in interference neighborhood to jointly serve users, thus the EE is improved. Hence after initialization, the defined merge and split operations are performed to iteratively obtain the optimal network partition. At each iteration, the proposed energy efficient beamforming algorithm (Algorithm 1) is used to determine the cooperative transmission strategy and calculate the achieved EE. In this way, we can obtain the EE optimal clusters and corresponding beamformers through hierarchical iteration. The detailed procedure is summarized in Algorithm 2.

Combing Algorithm 1 and 2, it can be seen that the proposed hierarchical iterative algorithm can be divided into three stages: Firstly, the cluster decision is initialized, then an iteration consisting of a number of successive merge operations is repeated until the partition converges, which results in a final EE optimal partition Q^*. During the iterations, the energy efficient beamforming is performed for each cluster decision to calculate the payoff. At last, the resulting partition tries to split if any is possible.

The resulting cluster decision is stable and no RRHs have incentive to deviate from current partition. In the following, we will show the convergence and stability of the proposed algorithm.

Algorithm 2 CFG-based energy efficient clustering algorithm

Initialize network partition as $Q^0 = \{\{1\}, \ldots, \{|\mathcal{Q}|\}\}$ and $h(\bar{Q})$;
repeat
  Select a cluster Q_k that haven't gone through merge operation;
  Finds the dominant interfere DI_k for cluster Q_k;
  Merge cluster DI_k and Q_k into a new cluster $\{\mathrm{DI}_k \cup Q_k\}$ and obtain a new partition Q';
  while $\{\mathrm{DI}_k \cup Q_k\} \notin h(\bar{Q})$ **do**
    Calculate the payoff of $\{\mathrm{DI}_k \cup Q_k\}$ based on the Algorithm 1;
    if $\{\mathrm{DI}_k \cup Q_k\} \triangleright_p \{\mathrm{DI}_k, Q_k\}$ **then**
      Keep the merge operation and update the network partition as $Q^* \leftarrow Q'$;
    end if
  end while
until Network partition converges;
The clusters in the final partition Q^* try to split if possible.

Proposition 4 *The proposed algorithm always converges with any initial partition.*

Proof The total number of the network partitions is finite, i.e., Bell number. Besides, By introducing history clustering information, repetitive deviations are avoided. Hence the proposed clustering algorithm is guaranteed to converges regardless of the initial partition. □

Proposition 5 *The partition Q^* that results from the proposed CFG-based energy efficient clustering algorithm is $\mathbb{D}_{hp}$-stable.*

Proof For a partition Q in coalition formation game, it is said to be $\mathbb{D}_{hp}$-stable, if no members in Q have incentive to leave their current coalition. According to Theorem 6.2 in [39], a partition is $\mathbb{D}_{hp}$-stable if and only if it is the outcome of the iterative merge and split operations. Hence, the partition Q^* is $\mathbb{D}_{hp}$-stable. □

Proposition 6 *The partition Q^* that results from the proposed CFG-based energy efficient clustering algorithm is $\mathbb{D}_p$-stable.*

Proof According to Theorem 10 [37], a partition Q is $\mathbb{D}_p$-stable if it is $\triangleright_p$-maximal. As discussed in Proposition 3, due to the cooperative structure, each cluster in the partition resulted from the proposed algorithm only contains RRHs which interfere each other. Hence, any possible partition $\tilde{Q}$, that leads to the optimal EE which is different from Q^*, is Q^*-homogeneous. In addition,according to Proposition 5, the resulting partition Q^* is $\mathbb{D}_{hp}$-stable. Therefore $Q^* \triangleright_p \tilde{Q}$ holds for any $\tilde{Q}$, namely, Q^* is Paretomaximal. To this end, the resulting partition Q^* is $\mathbb{D}_p$-stable. □

5 Numerical results

In this section, the performance of the proposed energy efficient clustering and beamforming algorithm for Cloud-RAN are numerically evaluated.

5.1 Simulation setup

As shown in Fig. 4, we consider a Cloud-RAN system that consists of 8 uniformly distributed RRHs each equipped with 2 antennas. Users are firstly attached to RRH whose pilot signal is strongest. At each time slot, we assume that each RRH only serves one single-antenna user. The simulated channel from RRH q_l to user i_k is as follows: (i) The pathloss model: $15.3 + 37.6 \log_{10}(d_{i_k}^{q_l})$, where $d_{i_k}^{q_l}$ in m denotes the distance between RRH q_l and user i_k. (ii) The small scale fading coefficient $\mathbf{h}_{i_k}^{q_l}$ is modeled as the Gaussian distribution with zero mean and unit covariance. (iii) Shadow fading is modeled by a log-normal distribution with zero mean and 8 dB variance. The adopted power consumption model of Cloud-RAN is described in section 2 and the relevant parameters are listed in Table 1.

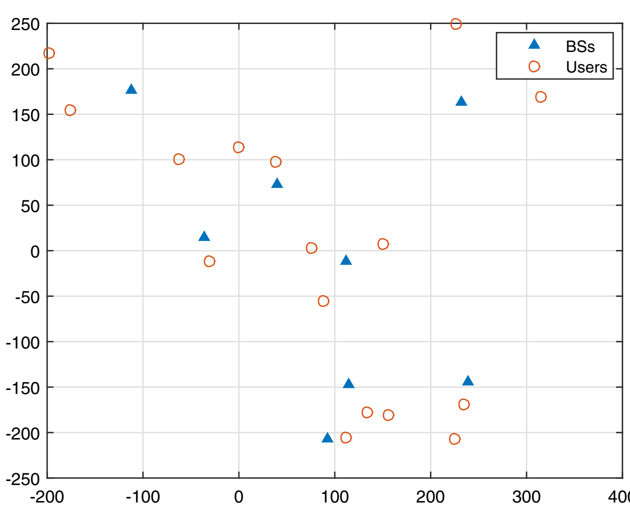

Fig. 4 Simulated network model

5.2 Convergence behavior of the proposed algorithms

We first show the convergence of the proposed algorithms. A framework utilizing hierarchical iterative algorithm is proposed in this paper to solve the energy efficient clustering and beamforming problem for Cloud-RAN. As summarized in section 3, the iterative process are utilized to obtain both the optimal beamformers and the EE. So the convergence rate of the two iterative process is vital for the implementation of proposed framework. Figure 5 shows the convergence behavior of the inner iterative loop in algorithm 1 for configuration $p_{q_k} = 21$dBm, $\forall q_k \in \mathcal{Q}$. It can be seen that the normalized error of beamformers quickly decreased to the acceptable region. Figure 6 shows the EE convergence behavior in algorithm 1, from which we can observe that EE converges fast with different transmit power constraint. In addition, the optimal cluster partition is obtained by algorithm 2. Figure 7 plots the required number of iterations for algorithm 2 to converge over 100 channel realizations. It can be seen that the proposed algorithm 2 converges fairly fast for most channel realizations. According to the discussion in Proposition 4 , and further considering the limited number of RRHs, algorithm 2 hence can converge fast regardless with any partition initialization.

5.3 Performance comparison

We evaluate the performance of the proposed framework in this subsection. For comparison, some baseline strategies are also simulated:

(i) the proposed energy efficient beamforming algorithm without any cooperation, termed as EEBA.
(ii) the proposed energy efficient beamforming algorithm with full cooperation, termed as EEBA-Full Cooperation.
(iii) the maximum ratio transmitter (MRT) [40] with no cooperation, termed as MRT.

Table 1 Parameters for power consumption model

Parameter	Value	Parameter	Value
$p_k^{sp,c}$	5.9 W	P_{sp}	6.7 W
a_1	0.68 W	a_2	0.2 W
C_{fh}	100 Mbps	T_s	66.7 µs
p	1.02	q	1.05

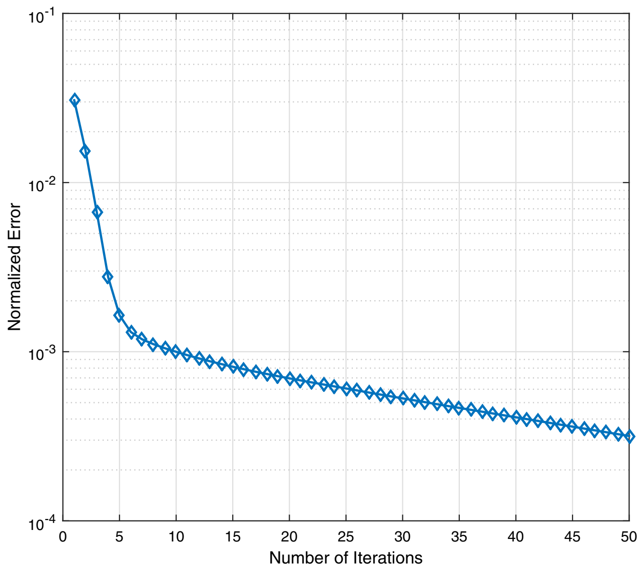

Fig. 5 Convergence behavior of the inner iterative loop in algorithm 1.

(iv) MRT with the proposed clustering algorithm, termed as MRT-EECA.

(v) MRT with full cooperation, termed as MRT-Full Cooperation.

Figure 8 shows the EE with different transmit power constraint. It can be seen that in the case where there don't exist multicell cooperation, applying the proposed energy efficient beamforming algorithm, the EE can be greatly improved compared with MRT strategy and the gain can be up to 56.52 %. In the case where energy efficient clustering algorithm is adopted, the proposed beamforming algorithm also achieves considerable EE gain against the MRT strategy. Therefore, we can conclude that whether the cooperation is employed, the algorithm always shows superior performance. This is due to the fact that MRT is a simple strategy that only beamforming in the same direction as the channel. In contrast, the proposed beamforming algorithm focuses on network EE optimization and hence shows better performance. Moreover, comparing with the case when MRT strategy and the proposed energy efficient clustering algorithm are jointly adopted, the EEBA also shows a superior performance. This observation indicates that to enable the flexible and efficient multiell cooperation, the beamforming strategy plays another vital role except efficient clustering strategy. In addition, it can be seen that with the increase of per-RRH transmit power constraint, the EE of all strategies first increases and then starts to drop. The reason is that in the low signal noise ratio (SNR) region, the circuit, signal processing and backhaul power consumption

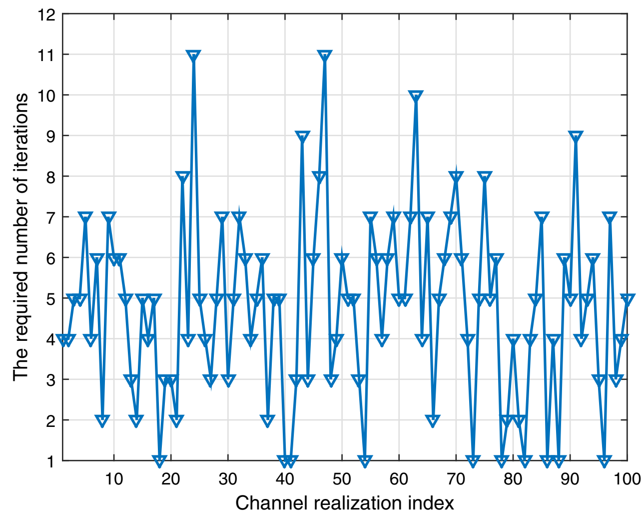

Fig. 7 Convergence behavior of algorithm 2.

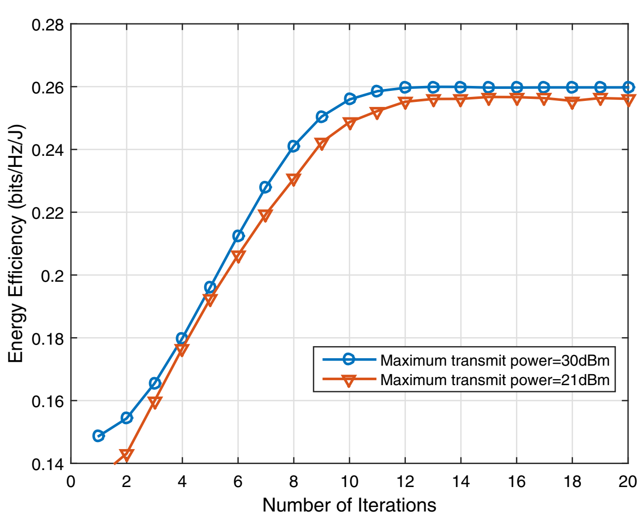

Fig. 6 Convergence behavior of the outer iterative loop in algorithm 1.

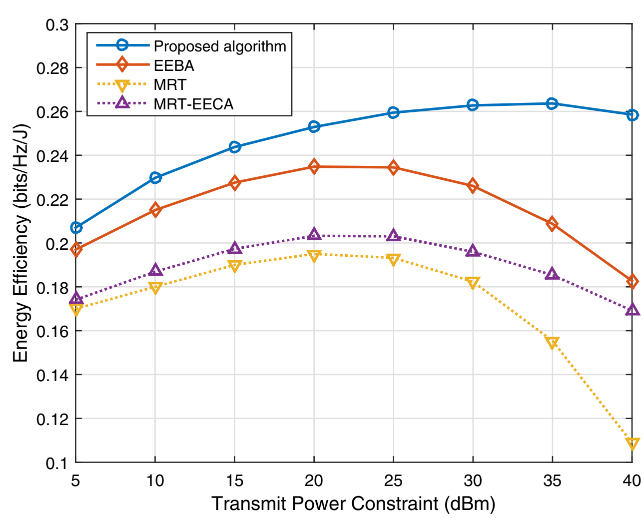

Fig. 8 EE under different transmit power constraint: performance demonstration of the proposed energy efficient beamforming algorithm

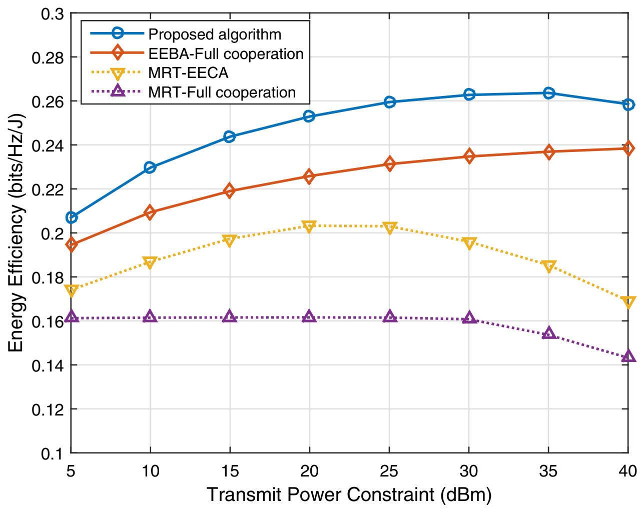

Fig. 9 EE under different transmit power constraint: performance demonstration of the proposed energy efficient clustering algorithm

dominates the total power cost, hence the capacity gain of the strategies can compensate the negative impact of the transmit power growth. However, in the high SNR region, the high total power cost share of transmit power makes the capacity gain cannot compensate the increase of transmit power, resulting in the drop down of the EE curves.

Figure 9 shows the impact of cooperation degree on the EE under different transmit power constraint. It can be easily obtained that our proposed algorithm outperforms other strategies with any transmit power constraint. For the case when EEBA is adopted, the proposed EECA can further improve the EE as shown in Fig. 8. Especially in high SNR region, the gain can be up to 44.4 %. Comparing with the full cooperation strategy, the EECA also always achieve higher EE. Moreover, when the proposed EECA is implemented together with MRT, the EE can also achieve a 28.1 % enhancement. Since when the transmit power of RRH increases, the ICI becomes increasingly severe. Generally, the interference of each cell is dominated by several RRHs, so the careful choose of cluster partition is of great importance for the EE optimization. Inappropriate RRHs cooperation will lead to limited capacity gain and hence can't compensate the negative impact caused by the growth of signal processing and backhaul power cost. We can see that with cooperation, the EE in high SNR region can be greatly enhanced. This is because that multicell cooperation can well handle the ICI and hence brings significant capacity gain. However, though the full cooperation can greatly improve the EE in high SNR region, it consumes more energy than the EECA strategies. Hence full cooperation results in lower EE. Comparing with full cooperation, the proposed EECA enables more flexible cooperation. When the ICI is severe, mutually interfering RRHs are encouraged to cooperate with each other to improve the

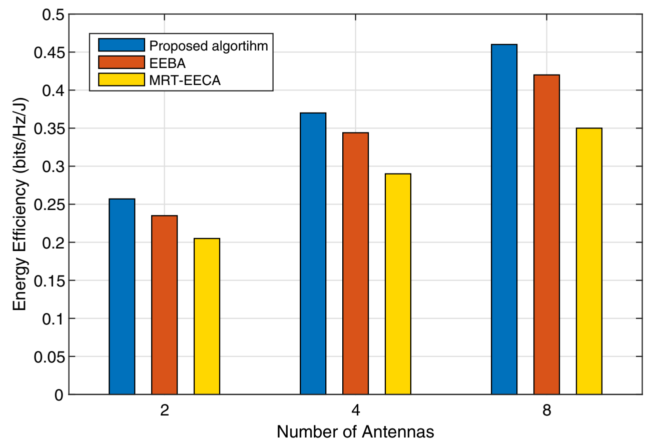

Fig. 10 Energy efficiency performance comparison under different antenna number configuration

EE. Hence the proposed algorithm always shows superior performance.

5.4 Impact of antenna number

In the above discussion, we set antenna number of each RRH to 2 for simplicity. However, as analyzed in [41], the antenna number has an important impact on the system efficiency, hence we would like to evaluate the impact of antenna number on the proposed algorithms. Figure 10 shows the EE performance comparison under different antenna number configuration. It can be seen that for each strategy, the energy efficiency monotonically increases with the growth of antenna number M at RRHs. This is because of the increased multiplexing gains. Moreover, we can see that for each antenna configuration, the proposed algorithm always show superior performance against other strategies. The performance gap grows with the increased antenna number. The proposed algorithm focuses on EE aware clustering and beamforming, since shows significant performance gain especially in high degree of freedom case.

6 Conclusion

In this paper, we considered joint clustering and beamforming for energy efficiency optimization in Cloud-RAN. In the dense network scenario, each RRHs separately serve their attached users may not be energy efficient due to the severe intercell interference. So some RRHs may be prompted to cooperative with interfering neighbor RRHs in order to improve the energy efficiency. Hence in this paper, the hierarchical iterative strategy is proposed to fulfill the goal of flexible cooperation. The EE optimization problem is divided into two coupled subproblem. CFG is used to obtain the EE-optimal network partition. On the other hand, based on the fractional program and the MMSE model, the EE optimization problem is transformed to a convex optimization problem and is efficiently solved. For the future work, we will consider the user scheduling and extend the algorithm into heterogeneous cloud radio access networks.

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