

Energy-Efficient On-demand Cloud Radio Access Networks Virtualization

Qiang Liu, Tao Han

The University of North Carolina at Charlotte
Charlotte, NC, United States
Email: {qliu12, tao.han}@uncc.edu

Nirwan Ansari

New Jersey Institute of Technology
Newark, NJ, United States
Email: nirwan.ansari@njit.edu

Abstract—By leveraging the elasticity of cloud computing, cloud radio access network (C-RAN) facilitates on-demand radio and computing resource provisioning. In this paper, we propose an energy-efficient on-demand C-RAN virtualization model which dynamically provisions virtual C-RAN according to service demand. The energy consumption of the virtual C-RAN is minimized by jointly optimizing the remote radio head (RRH) selection and computing resource provisioning. The network energy consumption minimization problem is challenging because of the interdependence between the RRH selection and the computing resource provisioning. We propose the energy-efficient on-demand C-RAN virtualization (REACT) algorithm to solve the problem in two steps. First, we cluster RRHs into groups using the hierarchical clustering analysis (HCA) algorithm and assign a BBU to each RRH group for the baseband signal processing. Second, we determine the RRH selection by optimizing the cooperative beamforming. The performance of the proposed algorithm is evaluated through extensive simulations, which shows the proposed algorithm reduces up to 62% of the network energy consumption as compared to a baseline algorithm.

Index Terms—C-RAN; Energy efficiency; Network virtualization; Cooperative beamforming;

I. INTRODUCTION

Mobile data traffic has been growing exponentially that calls for fifth generation mobile communication system (5G) to support massive connections with higher data rates, lower latency, ultra-higher reliability and higher energy efficiency [1], [2]. Taking advantages of cloud computing, cloud radio access network (C-RAN) is one of the most promising technologies for 5G. In C-RAN, the baseband signal is processed in the virtual baseband unit (vBBU) pool which is implemented using the cloud computing platform [3]. Owing to the centralized baseband signal processing, the channel state information (CSI) can be efficiently obtained to mitigate the interference among densely deployed remote radio heads (RRHs) [4]. As a result, C-RAN promises a better spectrum and energy efficiency.

Optimizing C-RAN energy efficiency attracts many research activities [5], [6]. The existing works can be classified into three categories. The first one is to minimize the energy consumption of RRHs. Tang *et al.* [7] proposed a cross-layer resource allocation method to reduce the energy consumption of RRHs by jointly optimizing the RRH selection and beamforming. Liu *et al.* [8], [9] improved the network energy efficiency of C-RAN by designing the radio resource allocation and RRH sleep mode control algorithm.

The second category of solutions is to minimize the energy consumption of vBBUs. Sigwele *et al.* [10] proposed a green intelligent traffic and resource elastic energy (iTREE) scheme to reduce the energy consumption of the BBU pool by matching the number of operating BBUs with the required baseband signal processing capacities. Pompili *et al.* [11] proposed an elastic resource utilization framework, trying to adapt the vBBU capacity to the fluctuations of network traffic. In this framework, RRHs are grouped into several virtual base station clusters (VBS-clusters) which are mapped to vBBUs to improve the energy efficiency and computing resource utilization.

The third category of solutions is to jointly optimize the energy consumption of RRHs and vBBUs. Chen *et al.* [12] proposed to reduce the energy consumption of RRHs and BBUs by optimizing the cooperative beamforming and RRH clustering. The cooperative beamforming problem is addressed by using the network-wide weighted minimum mean square error (WMMSE) approach while the RRH clustering is designed based on the coalition formation game. Wang *et al.* [13] proposed to jointly optimize the cooperative beamforming and the number of active BBUs. By assuming that the BBU capacity is given, they tried to minimize the number of BBUs based on a bin packing algorithm.

Based on the concept of cloud computing, C-RAN naturally supports network function virtualization (NFV) technologies [14]. However, the energy-efficient C-RAN virtualization is still an open problem. Existing energy-efficient C-RAN solutions focus on reducing the energy consumption rather than building a virtual network. Therefore, these solutions are not appropriate to realize energy-efficient on-demand C-RAN virtualization.

In this paper, we study the energy-efficient on-demand C-RAN virtualization, which minimizes the energy consumption of virtual C-RAN through jointly optimizing the vBBU provisioning and RRH selection. We formulate the energy-efficient C-RAN virtualization problem with the consideration of the network energy consumption and multiple practical constraints such as the minimum data rate of UEs and maximum transmission power of RRHs. Owing to the coupling between the vBBU provisioning and RRH selection, it is challenging to solve the C-RAN virtualization problem. We propose the energy-efficient on-demand C-RAN virtualization (REACT) algorithm to solve the problem in

two steps. Since the required computation capacity in a vBBU depends on the number of RRHs associated with the vBBU, it is essential to derive the RRH-vBBU association. Therefore, in the first step, we design a RRH grouping algorithm based on the hierarchical clustering analysis (HCA). The proposed RRH grouping algorithm clusters RRHs into groups according to the channel state information. Then, a vBBU is provisioned for each group of RRHs. In the second step, we determine the RRH selection. Given the provisioned vBBU, the active RRH is selected via solving a RRH selection and cooperative beamforming problem by an l_0 -norm approximation method. The performance of the proposed REACH algorithm is evaluated through network simulations.

The remainder of this paper is organized as follows. In Section II, we describe the system model and formulate the problem. In Section III, we develop the REACT algorithm to solve the energy-efficient on-demand C-RAN virtualization problem. In Section IV, we evaluate the performance of the proposed algorithm with extensive simulations. Finally, we conclude our work in Section V.

II. SYSTEM MODEL

In this section, we present the system model and formulate the energy-efficient C-RAN virtualization problem.

A. Network Model

We consider the downlink transmission in a C-RAN that consists of multiple RRHs and user equipment (UEs) as shown in Fig. 1. The sets of RRHs and UEs are denoted as \mathcal{L} and \mathcal{K} , respectively. We assume that there are M antennas installed in a RRH while a UE only has one antenna. Denote $\mathcal{G} = \{\mathcal{G}_1, \mathcal{G}_2, \dots\}$ as the set of the RRH groups. Here, $\mathcal{G}_i \cap \mathcal{G}_j = \emptyset, \forall i, j \in \{1, 2, \dots, |\mathcal{G}|\}$ and $\bigcup_{n=1}^{|\mathcal{G}|} \mathcal{G}_n = \mathcal{L}$. The RRHs in a group serve their associated UEs through cooperative beamforming. A vBBU is provisioned for each group of RRHs to conduct the baseband signal processing. RRHs are connected to the vBBU pool by optical-fiber fronthaul which has sufficient capacity and negligible latency. We assume that perfect channel state information (CSI) can be obtained in the vBBU pool for the resource management [15]. UE is associated with the RRH based on the received reference power.

We denote $\mathbf{w}_{l,k} \in \mathbb{C}^{M \times 1}$ as the downlink beamforming vector from the l th RRH to the k th UE. Assume that the k th UE is associated with a RRH belonging to the m th RRH group. Using the linear transmit beamforming scheme, the received signal at the k th UE can be calculated as

$$y_k = \sum_{l \in \mathcal{G}_m} \mathbf{H}_{l,k} \mathbf{w}_{l,k} s_k + \underbrace{\sum_{l \notin \mathcal{G}_m} \sum_{j \in \mathcal{K}} \mathbf{H}_{l,k} \mathbf{w}_{l,j} s_j}_{\text{inter-group interference}} + \underbrace{\sum_{l \in \mathcal{G}_m} \sum_{j \neq k, j \in \mathcal{K}} \mathbf{H}_{l,k} \mathbf{w}_{l,j} s_j}_{\text{intra-group interference}} + n_k, \quad (1)$$

where $\mathbf{H}_{l,k} \in \mathbb{C}^{1 \times M}$ denotes the channel vector from the l th RRH to the k th UE, and n_k is the received noise at the

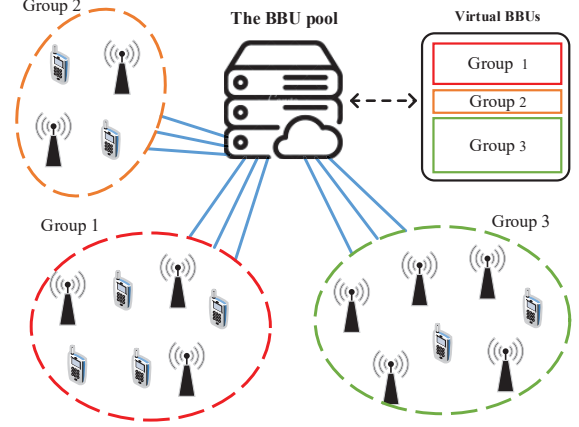


Figure 1. An illustration of virtual C-RAN. RRHs are connected to the vBBU pool by fronthaul and clustered into several groups for cooperative signal processing in vBBUs.

k th UE. We assume UEs' signals follow the independent and identically distribution, $\mathcal{CN}(0, 1)$, and each UE has a single data stream. Therefore, the achievable data rate for the k th UE can be written as

$$R_k = B_0 \log \left(1 + \frac{\sum_{l \in \mathcal{G}_m} \mathbf{H}_{l,k} \mathbf{w}_{l,k} (\mathbf{w}_{l,k})^H (\mathbf{H}_{l,k})^H}{I_k + \sigma^2} \right), \quad (2)$$

where σ^2 is the power of the additive white Gaussian noise (AWGN), B_0 is the system bandwidth, and $(\bullet)^H$ is the Hermitian transpose. I_k is the summation of the inter-group and intra-group interference and can be expressed as

$$I_k = \sum_{l \notin \mathcal{G}_m} \sum_{j \in \mathcal{K}} \mathbf{H}_{l,k} \mathbf{w}_{l,j} (\mathbf{w}_{l,j})^H (\mathbf{H}_{l,k})^H + \sum_{l \in \mathcal{G}_m} \sum_{j \neq k, j \in \mathcal{K}} \mathbf{H}_{l,k} \mathbf{w}_{l,j} (\mathbf{w}_{l,j})^H (\mathbf{H}_{l,k})^H. \quad (3)$$

B. Energy Consumption Model

The energy consumption model of C-RAN is determined by the energy consumption of the vBBU pool, fronthaul and RRHs. Therefore, the C-RAN energy consumption model can be expressed as

$$P^T = \sum_{n=1}^{|\mathcal{G}|} P_n^S + \sum_{l \in \mathcal{L}} P_l^F + \sum_{l \in \mathcal{L}} P_l^R, \quad (4)$$

where P_n^S , P_l^F and P_l^R represent the energy consumption of the n th vBBU, the l th fronthaul, and the l th RRH, respectively.

On modeling the energy consumption of RRHs, we assume that a RRH operates in either the active mode or the sleep mode. In the active mode, the power consumption of RRH consists of the static and dynamic power consumption [16]. When a RRH is in the sleep mode, it only consumes a small

amount of power. Hence, the power consumption of the l th RRH can be expressed as

$$P_l^R = \begin{cases} P_l^{R,A} + \frac{1}{\eta} \sum_{k \in \mathcal{K}} \|\mathbf{w}_{l,k}\|_2^2, & S_l \neq 0, \\ P_l^{R,S}, & S_l = 0, \end{cases} \quad (5)$$

where $P_l^{R,A}$ and $P_l^{R,S}$ are the power consumption of the l th RRH in the active and sleep modes, respectively. $S_l = \sum_{k \in \mathcal{K}} \|\mathbf{w}_{l,k}\|_2^2$ indicates whether the l th RRH is selected for the virtual network. If $S_l = 0$, the l th RRH is not selected; otherwise, it is selected. η is a factor that reflects the efficiency of the power amplifier in the RRH.

The energy consumption of the fronthaul is closely related to its traffic load [15]. Hence, the energy consumption of fronthaul of the l th RRH is formulated as

$$P_l^F = P_l^{F,A} + \sum_{k \in \mathcal{K}_l} f(R_k), \quad (6)$$

where $P_l^{F,A}$ is the active power of the fronthaul of the l th RRH, and \mathcal{K}_l is the set of UEs associated with the l th RRH. $f(R_k)$ is a non-negative and non-decreasing function characterizing the dynamic power consumption of the fronthaul. For example, $f(R_k) = \kappa R_k$ [15], where κ is a constant parameter.

The power consumption of a vBBU also consists of the static and dynamic power consumption. The static power is the power required to keep the vBBU in the active mode. The dynamic power consumption is related to the number of RRHs in the associated RRH group [17]. More dynamic energy is consumed when the vBBU serves a larger number of RRHs. Hence, we formulate the energy consumption of the n th vBBU as

$$P_n^S = P_n^{S,A} + g(|\mathcal{G}_n|), \quad (7)$$

where $P_n^{S,A}$ and $g(|\mathcal{G}_n|)$ represent the static and dynamic power consumption of the n th vBBU, respectively. $g(|\mathcal{G}_n|)$ is modeled as a quadratic function, $g(|\mathcal{G}_n|) = a|\mathcal{G}_n| + b|\mathcal{G}_n|^2$, where a and b are constant parameters [12], [17].

Based on the above analysis, the network energy consumption of C-RAN, Eq. (4) can be rewritten as

$$\begin{aligned} P^T &= P^{\text{static}} + \frac{1}{\eta} \sum_{l \in \mathcal{L}} \sum_{k \in \mathcal{K}} \|\mathbf{w}_{l,k}\|_2^2 + \sum_{k \in \mathcal{K}} f(R_k) \\ &+ \sum_{l \in \mathcal{L}} (P_l^{R,A} - P_l^{R,S}) \|S_l\|_0 + \sum_{n=1}^{|\mathcal{G}|} (P_n^{S,A} + g(|\mathcal{G}_n|)) \end{aligned} \quad (8)$$

where $P^{\text{static}} = \sum_{l \in \mathcal{L}} (P_l^{R,S} + P_l^{F,A})$. The $\|\bullet\|_0$ is the l_0 -norm which calculates the number of non-zero elements in a vector.

C. Problem Formulation

In order to build a virtual C-RAN, we have to select RRHs for transmitting and receiving radio frequency (RF) signals and provision vBBUs for processing baseband signals. The computation capacity of a vBBU is limited by its hardware such as the CPU and memory. Therefore, multiple vBBUs are required to serve RRHs. In this case, RRHs are clustered

Algorithm 1 The RGBP Algorithm

- 1: **Input:** The channel matrix \mathbf{H} ;
 - 2: **Output:** The RRH grouping \mathcal{G}^* ;
 - 3: **Initialize** the RRH groups as $\mathcal{G}(0) = \{\{1\}, \{2\}, \dots, \{|\mathcal{L}|\}\}$;
 - 4: **for** $k=1:|\mathcal{L}|-1$ **do**
 - 5: Find the two different groups \mathcal{G}_m and \mathcal{G}_n such that $Q_{m,n} = \arg \max_{i,j \in \{1,2,\dots,|\mathcal{G}|\}} Q_{i,j}$;
 - 6: Cluster \mathcal{G}_m and \mathcal{G}_n into a group;
 - 7: Save the current RRH groups $\mathcal{G}(k)$ and the vBBU energy consumption $P^S(k) = \sum_{n=1}^{|\mathcal{G}|} P_n^S$ calculated by Eq. (7);
 - 8: **end for**
 - 9: Find $P^* = \arg \max_{1 \leq k \leq |\mathcal{L}|-1} P^S(k)$ and corresponding RRH groups \mathcal{G}^* ;
-

into groups, and each group of RRHs is served by a vBBU. Therefore, the number of RRH groups determines how many vBBUs are required in the virtual C-RAN.

Minimizing the number of RRH groups, however, incurs a higher computation demand in individual vBBUs. The number of active RRHs connected to a vBBU determines the computation demand in the vBBU. If RRHs are clustered in a small number of groups, the number of RRHs in each group will be large. As a result, an individual vBBU needs a larger computation capacity to serve the associated RRHs and thus consumes more power. Hence, a proper RRH group is essential for the C-RAN virtualization. After the vBBUs are virtualized, dynamically selecting the serving RRHs can further reduce the energy consumption of the virtual network. The dynamic RRH selection can be realized via optimizing the cooperative beamforming.

The energy-efficient on-demand C-RAN virtualization problem is thus formulated as

$$\begin{aligned} \mathcal{P}1: \quad & \min_{\{\mathcal{G}, \mathbf{W}\}} P^T \\ & s.t. \\ & C_1: R_k \geq r_k^{\min}, \forall k \in \mathcal{K}, \\ & C_2: \sum_{k \in \mathcal{K}} \|\mathbf{w}_{l,k}\|_2^2 \leq P_l^{\max}, \forall l \in \mathcal{L}, \\ & C_3: \mathcal{G}_m \cap \mathcal{G}_n = \emptyset, \forall \mathcal{G}_m, \mathcal{G}_n \in \mathcal{G}, \\ & C_4: \bigcup_{n=1}^{|\mathcal{G}|} \mathcal{G}_n = \mathcal{G}, \end{aligned} \quad (9)$$

where $\mathbf{W} = \{\mathbf{w}_{l,k} | l \in \mathcal{L}, k \in \mathcal{K}\}$ is the cooperative beamforming matrix, r_k^{\min} is the minimum data rate of the k th UE, and P_l^{\max} is the maximum transmission power of the l th RRH. C_1 reflects the minimum data rate constraints of UEs, and C_2 are the maximum transmission power constraint of RRHs. C_3 and C_4 are the intrinsic restrictions of the RRH grouping.

The non-convex objective function and integer variables make problem $\mathcal{P}1$ a highly complex mixed integer non-linear programming problem, which lacks efficient solutions [18]. In the following sections, we design a heuristic algorithm to approximate the optimal solution to the problem.

III. THE REACT ALGORITHM

In this section, we present the energy-efficient on-demand C-RAN virtualization (REACT) algorithm to solve Problem $\mathcal{P}1$. The coupling of the RRH grouping and cooperative beamforming is the key challenge in solving Problem $\mathcal{P}1$. Owing to the dense RRH deployment, it is impractical to calculate the cooperative beamforming for entire RRHs in the network. Hence, RRHs should be clustered into groups, and cooperative beamforming is derived for RRHs in the same group. If the RRH groups are given, the cooperative beamforming problem can be solved by using the second order conic programming [19]. However, the RRH grouping depends on whether the cooperation between the RRHs can improve the network performance. In other words, the solution to the cooperative beamforming problem provides useful information for the RRH grouping.

We propose to decompose Problem $\mathcal{P}1$ by exploring the relationship between the cooperative beamforming and channel state information. The optimal cooperative beamforming is derived based on channel state information. Hence, the channel state information can be exploited to determine the RRH grouping. Therefore, Problem $\mathcal{P}1$ is decomposed into two subproblems: the RRH grouping problem ($\mathcal{P}2$) and the cooperative beamforming problem ($\mathcal{P}3$). On solving Problem $\mathcal{P}2$, we cluster RRHs into groups based on the channel state information and derive the number of vBBUs. Given the RRH groups, we address Problem $\mathcal{P}3$ to obtain the RRH selection.

A. RRH Grouping and vBBU Provisioning

In this part, we solve the RRH grouping and vBBU provisioning problem $\mathcal{P}2$. On grouping the RRHs, we aim to minimize the network energy consumption. The number of RRH groups and the size of individual groups determines the energy consumption of vBBUs. Meanwhile, the intra-group channel quality and the inter-group interferences impact the energy consumption of the RRHs and the corresponding fronthaul links. We design a RRH grouping algorithm based on the hierarchical clustering analysis (HCA) method which agglomerates a set of RRHs into a hierarchy of groups [20]. The advantage of HCA over other algorithms such as K-means [21] is that it does not require a prior knowledge of the number of groups, which cannot be predefined due to complex wireless channel and mobile traffic dynamics [11].

In the HCA-based algorithms, the distance function is very important for achieving the optimal grouping. In order to improve the intra-group channel quality and suppress the inter-group interference, we adopt the average channel quality (ACQ) as the distance function. Denote \mathcal{L}_i and \mathcal{K}_i as the set of RRHs in the i th group and the set of UEs associated with those RRHs, respectively. The ACQ between the i th and j th group $Q_{i,j}$ is defined as

$$Q_{i,j} = Q_{j,i} = \frac{1}{2} (d_{i,j} + d_{j,i}), \quad (10)$$

where

$$d_{m,n} = \frac{1}{|\mathcal{K}_m| |\mathcal{L}_n|} \sum_{i \in \mathcal{L}_m} \sum_{j \in \mathcal{K}_n} \|\mathbf{H}_{i,j}\|_2^2. \quad (11)$$

The pseudo code of the RRH grouping and vBBU provisioning (RGBP) algorithm is presented in Alg. 1. At the beginning, each RRH is recognized as an individual group. Based on the defined distance function, the groups with the maximum distance are merged into one group in each iteration. After the groups are merged, we calculate the network energy consumption. The optimal RRH grouping is derived when the network energy consumption is minimized.

B. Cooperative Beamforming and RRH Selection

Assume that the RRHs are clustered in N groups. Given the RRH grouping, the cooperative beamforming and RRH selection problem ($\mathcal{P}3$) can be decomposed into N subproblems. That is, each group of RRHs can calculate their beamforming independently. Denote \mathcal{L}_n as the set of the n th group of RRHs. Let \mathcal{K}_n be the set of UEs associated with the n th group of RRHs. The n th subproblem \mathcal{P}_n can be expressed as

$$\begin{aligned} & \min_{\{\mathbf{W}_n\}} P_n^T \\ & \text{s.t.} \\ & C_{n1}: R_k \geq r_k^{\min}, \forall k \in \mathcal{K}_n, \\ & C_{n2}: \sum_{k \in \mathcal{K}_n} \|\mathbf{w}_{l,k}\|_2^2 \leq P_l^{\max}, \forall l \in \mathcal{L}_n, \end{aligned} \quad (12)$$

where

$$\begin{aligned} P_n^T = P_n^{\text{static}} &+ \frac{1}{\eta} \sum_{l \in \mathcal{L}_n} \sum_{k \in \mathcal{K}_n} \|\mathbf{w}_{l,k}\|_2^2 + \sum_{k \in \mathcal{K}_n} f(R_k) \\ &+ \sum_{l \in \mathcal{L}_n} (P_l^{R,A} - P_l^{R,S}) \|S_l\|_0, \end{aligned} \quad (13)$$

is the energy consumption of the n th group, and

$$P_n^{\text{static}} = \sum_{l \in \mathcal{L}_n} (P_l^{R,S} + P_l^{F,A}) + P_n^{S,A} + g(|\mathcal{G}_n|). \quad (14)$$

\mathbf{W}_n is the cooperative beamforming vector of the RRHs in the n th group. The difficulty of solving the above problem lies in the non-convexity of the objective function and constraints.

The network energy consumption is non-decreasing with respect to the data rate. Since the objective is to minimize the network energy consumption, the optimal solution is always achieved when UEs' data rates equal to their required minimum data rates. Hence, the constraint C_{n1} in Problem \mathcal{P}_n is met with the equality at the optimal point. Therefore, Problem \mathcal{P}_n can be equivalently transformed into

$$\begin{aligned} \mathcal{P}4: & \min_{\{\mathbf{W}_n\}} \tilde{P}_n^T \\ & \text{s.t.} \quad C_{n1}, C_{n2}, \end{aligned} \quad (15)$$

where

$$\begin{aligned} \tilde{P}_n^T = P_n^{\text{static}} &+ \frac{1}{\eta} \sum_{l \in \mathcal{L}_n} \sum_{k \in \mathcal{K}_n} \|\mathbf{w}_{l,k}\|_2^2 + \sum_{k \in \mathcal{K}_n} f(r_k^{\min}) \\ &+ \sum_{l \in \mathcal{L}_n} (P_l^{R,A} - P_l^{R,S}) \|S_l\|_0. \end{aligned} \quad (16)$$

Here, R_k is replaced by r_k^{\min} .

Then, we convexify the non-convex constraints C_{n1} . Since the phase of \mathbf{w}_k does not change the objective function

Algorithm 2 The CBRs Algorithm

- 1: **Input:** The RRH grouping \mathcal{G}_n , the channel matrix \mathbf{H} ;
 - 2: **Output:** The cooperative beamforming \mathbf{W}_n^* and RRH selection \mathbf{S}_n^* of the n th group \mathcal{G}_n ;
 - 3: **Initialize** the weighted $\beta(0)$, convergence condition ε , set $i = 1$;
 - 4: **while** True **do**
 - 5: Solve the problem $\mathcal{P}5$ with approximated energy consumption \hat{P}_n^T and obtain the optimal $\mathbf{W}_n(i)$;
 - 6: **if** $|\beta_l(i) - \beta_l(i-1)|/\beta_l(i-1) \leq \varepsilon, \forall l \in \mathcal{L}_n$ **then**
 - 7: $\beta^* = \beta(i)$ and $\mathbf{W}_n^* = \mathbf{W}_n(i)$, **break**;
 - 8: **else**
 - 9: Update $\beta^{(i)}$ according to (19) and set $i = i + 1$;
 - 10: **end if**
 - 11: **end while**
 - 12: Determine the RRH selection \mathbf{S}_n^* based on (5).
-

and constraints of Problem $\mathcal{P}4$ [22], the constraints are equivalent to the second order conic (SOC) constraints as

$$\hat{C}_{n1} : \|\mathbf{I}_k\|_2 \leq \sqrt{1 + 1/(2^{\gamma_k} - 1)} \times \sum_{k \in \mathcal{K}_n} \text{Re}\{\mathbf{S}_k\}, \forall k \in \mathcal{K} \quad (17)$$

where $\mathbf{S}_k = [R_{ij}^k | i = k, j \in \mathcal{G}_m]^T$, $R_{ij}^k = \mathbf{H}_{k,j} \mathbf{w}_{i,j}$ and $\mathbf{I}_k = [R_{jk} | i \in \mathcal{K}_n, j \in \mathcal{L}_n; \sigma]^T$. $\text{Re}\{\cdot\}$ denotes the real part and $\gamma_k = r_k^{\min}/B_0$.

Next, we iteratively approximate the l_0 -norm in the network energy consumption model in Eq. (16). Since $S_l \geq 0$, based on the l_0 -norm approximation method [23], we have $\|S_l\|_0 \approx \beta_l S_l$, where β_l is the weight of the l th RRH. Then, the network energy consumption is rewritten as

$$\hat{P}_n^T = P_n^{\text{static}} + \sum_{k \in \mathcal{K}_n} f(r_k^{\min}) + \sum_{l \in \mathcal{L}_n} \Delta_l \sum_{k \in \mathcal{K}_n} \|\mathbf{w}_{l,k}\|_2^2, \quad (18)$$

where $\Delta_l = (P_l^{R,A} - P_l^{R,S})\beta_l + \frac{1}{\eta}$. Here, β_l is calculated as

$$\beta_l = \frac{\xi}{S_l + \tau}. \quad (19)$$

When calculating β_l , S_l is derived from the previous iteration. τ and ξ are the constants which regulate the stability and precision of the approximation. The value of β_l is iteratively updated based on Eq. (19) until it converges. The l_0 -norm approximation method is proved to be convergent if τ and ξ are appropriately selected [15].

After the above problem transformation, we obtain the approximated problem $\mathcal{P}5$ as

$$\mathcal{P}5 : \min_{\{\mathbf{W}_n\}} \hat{P}_n^T \quad (20)$$

$$\text{s.t.} \quad \hat{C}_{n1}, C_{n2}.$$

Problem $\mathcal{P}5$ is a second-order conic programming (SOCP) problem which can be effectively solved by optimization problem solvers, e.g., CVX [24].

The pseudo code in Alg. 2 summarizes the procedures of the proposed cooperative beamforming and RRH selection (CBRS) algorithm.

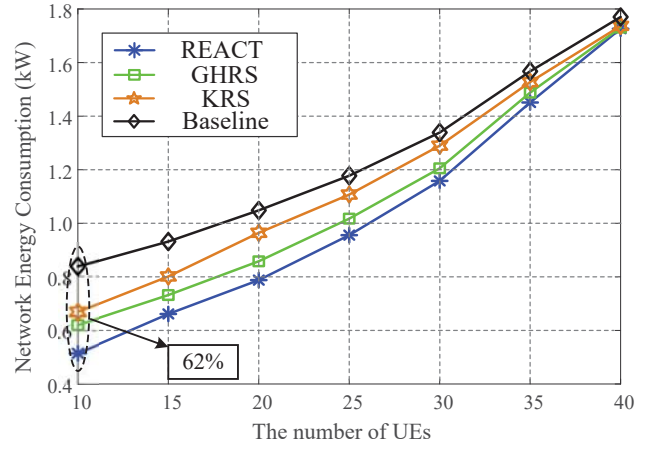


Figure 2. The network energy consumption versus the number of UEs.

IV. SIMULATION RESULTS AND ANALYSIS

In this section, the performance of the proposed REACT algorithm is evaluated through network simulations. In the simulation, 20 RRHs and 30 UEs are randomly distributed in a 500m \times 500m area. The distributions of both RRHs and UEs follow the Poisson point process (PPP). The maximum transmission power of RRHs P^{max} is 40dBm and $\eta = 0.36$ [16]. The system bandwidth B_0 is 10 MHz. The number of transmit antennas in a RRH is 2. The path loss between a RRH and a UE is modeled as $140.7 + 36.7 \log_{10}(d)$, where d denotes the distance between the RRH and UE in kilometers. σ^2 is -164dBm/Hz. Based on the energy consumption measurements [25], we set the default value of $P_l^{R,A}$, $P_l^{R,S}$, $P_n^{S,A}$ and $P_l^{F,A}$ to 18.5, 3.5, 12 and 10 Watt, respectively. The values of a , b , κ are 2.8, 0.5 and 1.85×10^{-7} , respectively. The minimum data rate requirement of a UE is 10Mbps.

In the simulation, we compare the performance of the proposed REACT algorithm with the following algorithms.

- **Baseline algorithm:** The baseline algorithm adopts K-means clustering algorithm [21] to group RRHs. In the K-means clustering algorithm, the number of clusters is predefined and the geo-distance between RRHs is defined as the distance function. The baseline algorithm activates all available RRHs.
- **K-means clustering with the RRH selection (KRS):** The KRS algorithm adopts the geo-distance based K-means algorithm to group RRHs, which is the same as the baseline algorithm. After the RRH grouping, the KRS algorithm uses the proposed CBRS algorithm to select the active RRHs.
- **Geo-distance based HCA with the RRH selection (GHRS):** The GHRS algorithm adopts the HCA algorithm to group RRHs. Here, the HCA algorithm uses the geo-distance between RRHs as the distance function for the clustering analysis. The GHRS algorithm also relies on the CBRS algorithm to select the active RRHs.

Fig. 2 shows the network energy consumption versus the number of UEs. In general, the virtual C-RAN consumes

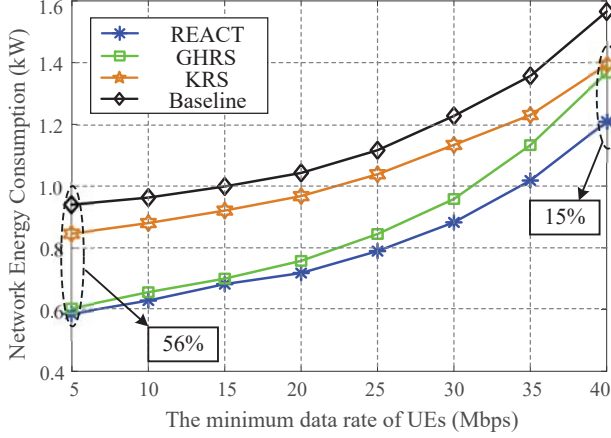


Figure 3. The network energy consumption versus the minimum data rate.

more energy when there are more UEs in the network. When the number of UEs in the network is small, fewer RRHs are required to serve the UEs. Therefore, when the number of UEs is small, the proposed REACT algorithm can save a significant amount of energy because of the dynamic RRH selection and vBBU provisioning. As shown in Fig. 2, the REACT algorithm outperforms the baseline algorithm by 62%. As compared with the KRS algorithm, both the GHRS and RGBP algorithms have better performance in terms of energy consumption. This means that the HCA algorithm can achieve a better RRH grouping that leads to a reduced network energy consumption. The observation indicates that a proper RRH grouping is very important to reduce energy consumption in the virtual C-RAN.

Figure 3 shows the network energy consumption versus the data rate requirement of UEs. When the minimum data rate is low, less vBBUs and RRHs are required in the virtual C-RAN. Therefore, the REACT, KRS, and GHRS algorithms achieve less energy consumption than the baseline algorithm does. The REACT and GHRS algorithms outperform the baseline algorithm by about 56% because of the advantages of the HCA grouping algorithm. As the minimum data rate increases, the REACT algorithm consumes about 15% less energy as compared with the GHRS algorithm. The performance gain is obtained from a better RRH grouping solution derived based on the REACT algorithm, which adopts the mean-channel quality as the distance function in the clustering analysis.

Fig. 4 shows the performance of different algorithms in terms of suppressing the interference. When RRHs are densely deployed, a UE may receive severe interference from the RRHs which do not serve the UE. A proper RRH grouping can efficiently suppress the interference. As shown in the figure, the REACT algorithm outperforms the other algorithms in suppressing the interference. This indicates that grouping RRHs based on the mean-channel quality is a more effective method in terms of reducing the average interference received by a UE.

We evaluate how the vBBU energy consumption model

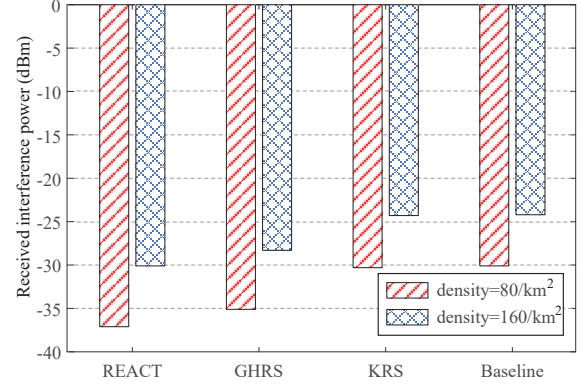


Figure 4. The received interference of UEs versus the density of RRHs.

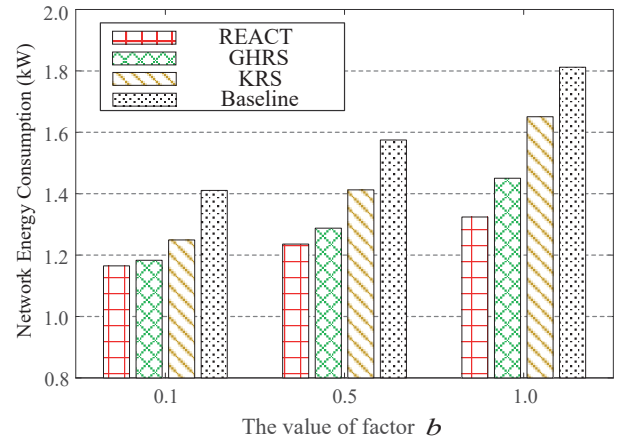


Figure 5. The network energy consumption versus the parameter, b .

impacts the network energy consumption. According to Eq. 7, the dynamic power consumption of the vBBU is determined by the size of the RRH group ($|\mathcal{G}_n|$). In the dynamic power consumption model, two parameters, a and b , defines the relationship between the dynamic power consumption of the size of the RRH group. Since b is the coefficient of the second-degree term, b plays a more important role in defining the relationship. Therefore, we evaluate the network energy consumption with different values of b while letting a be a constant. As shown in Fig. 5, a larger b results in a higher network energy consumption for all the algorithms. However, the network energy consumption with the proposed REACT algorithm increases much slower than that with the other algorithms. When b is large, the REACT algorithm will create more RRH groups to reduce the number of RRH in individual groups. Therefore, the energy consumption of the vBBU will be lowered. In addition, the REACT algorithm groups the RRHs based on the mean channel quality, which not only increases the intra-group channel quality but also reduces the inter-group interference. As a result, the REACT algorithm reduces the power consumption of RRHs and corresponding fronthaul links.

V. CONCLUSION

In this paper, we have investigated the energy-efficient on-demand C-RAN virtualization. We have formulated the energy-efficient C-RAN virtualization problem with consideration of multiple practical constraints such as the data rate requirements of UEs and maximum transmission power of RRHs. Our proposed energy-efficient on-demand C-RAN virtualization (REACT) algorithm jointly optimizes the vBBU provisioning and RRH selection in the virtual C-RAN. The performance of the proposed algorithm has been validated via network simulations, which shows the REACT algorithm significantly reduces the energy consumption of the virtual C-RAN.

ACKNOWLEDGEMENT

This work is partially supported by the U.S. National Science Foundation under Grant No. 1731675, No. 1810174 and the UNC-Charlotte Faculty Research Grant.

REFERENCES

- [1] I. F. Akyildiz, S. Nie, S.-C. Lin, and M. Chandrasekaran, "5G roadmap: 10 key enabling technologies," *Computer Networks*, vol. 106, pp. 17–48, 2016.
- [2] X. Guo, L. Li, N. Ansari, and B. Liao, "Accurate wifi localization by fusing a group of fingerprints via global fusion profile," *IEEE Transactions on Vehicular Technology*, 2018.
- [3] C. Mobile, "C-RAN: the road towards green RAN," *White Paper*, ver. vol. 2, 2011.
- [4] Q. Liu, T. Han, N. Ansari, and G. Wu, "On designing energy-efficient heterogeneous cloud radio access networks," *IEEE Transactions on Green Communications and Networking*, 2018.
- [5] H. Li, C. Yang, X. Huang, N. Ansari, and Z. Wang, "Cooperative ran caching based on local altruistic game for single and joint transmissions," *IEEE Communications Letters*, vol. 21, no. 4, pp. 853–856, 2017.
- [6] M. Yousefvand, T. Han, N. Ansari, and A. Khreishah, "Distributed energy-spectrum trading in green cognitive radio cellular networks," *IEEE Transactions on Green Communications and Networking*, vol. 1, no. 3, pp. 253–263, 2017.
- [7] J. Tang, W. P. Tay, and T. Q. Quek, "Cross-layer resource allocation with elastic service scaling in cloud radio access network," *IEEE Transactions on Wireless Communications*, vol. 14, no. 9, pp. 5068–5081, 2015.
- [8] Q. Liu, G. Wu, Y. Guo, Y. Zhang, and S. Hu, "Energy efficient resource allocation for control data separated heterogeneous-CRAN," in *Global Communications Conference (GLOBECOM)*, 2016 IEEE. IEEE, 2016, pp. 1–6.
- [9] Q. Liu, T. Han, and G. Wu, "Computing resource aware energy saving scheme for cloud radio access networks," in *Sustainable Computing and Communications (SustainCom)*, 2016 IEEE International Conferences on. IEEE, 2016, pp. 541–547.
- [10] T. Sigwele, P. Pillai, and Y. F. Hu, "iTREE: Intelligent traffic and resource elastic energy scheme for Cloud-RAN," in *Future Internet of Things and Cloud (FiCloud)*, 2015 3rd International Conference on. IEEE, 2015, pp. 282–288.
- [11] D. Pompili, A. Hajisami, and T. X. Tran, "Elastic resource utilization framework for high capacity and energy efficiency in cloud RAN," *IEEE Communications Magazine*, vol. 54, no. 1, pp. 26–32, 2016.
- [12] Y. Chen, X. Wen, Z. Lu, and H. Shao, "Energy efficient clustering and beamforming for cloud radio access networks," *Mobile Networks and Applications*, pp. 1–13, 2016.
- [13] K. Wang, W. Zhou, and S. Mao, "On joint bbu/rrh resource allocation in heterogeneous cloud-rans," *IEEE Internet of Things Journal*, 2017, doi:10.1109/JIOT.2017.2665550.
- [14] O. Simeone, A. Maeder, M. Peng, O. Sahin, and W. Yu, "Cloud radio access network: Virtualizing wireless access for dense heterogeneous systems," *Journal of Communications and Networks*, vol. 18, no. 2, pp. 135–149, 2016.
- [15] B. Dai and W. Yu, "Energy efficiency of downlink transmission strategies for cloud radio access networks," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 4, pp. 1037–1050, 2016.
- [16] G. Auer, O. Blume, V. Giannini, I. Godor, M. Imran, Y. Jading, E. Katranaras, M. Olsson, D. Sabella, P. Skillermark *et al.*, "D2. 3: Energy efficiency analysis of the reference systems, areas of improvements and target breakdown," *EARTH*, pp. 1–69, 2010.
- [17] F. Pantisano, M. Bennis, W. Saad, R. Verdone, and M. Latva-Aho, "On the dynamic formation of cooperative multipoint transmissions in small cell networks," in *Globecom Workshops (GC Wkshps)*. IEEE, 2012, pp. 1139–1144.
- [18] K. G. Murty and S. N. Kabadi, "Some NP-complete problems in quadratic and nonlinear programming," *Mathematical programming*, vol. 39, no. 2, pp. 117–129, 1987.
- [19] S. Boyd and L. Vandenberghe, *Convex optimization*. Cambridge university press, 2004.
- [20] S. C. Johnson, "Hierarchical clustering schemes," *Psychometrika*, vol. 32, no. 3, pp. 241–254, 1967.
- [21] J. A. Hartigan and M. A. Wong, "Algorithm AS 136: A k-means clustering algorithm," *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, vol. 28, no. 1, pp. 100–108, 1979.
- [22] Y. Shi, J. Zhang, and K. B. Letaief, "Group sparse beamforming for green Cloud-RAN," *IEEE Transactions on Wireless Communications*, vol. 13, no. 5, pp. 2809–2823, 2014.
- [23] E. J. Candes, M. B. Wakin, and S. P. Boyd, "Enhancing sparsity by reweighted ℓ_1 minimization," *Journal of Fourier analysis and applications*, vol. 14, no. 5-6, pp. 877–905, 2008.
- [24] M. Grant, S. Boyd, and Y. Ye, "CVX: Matlab software for disciplined convex programming," 2008.
- [25] D. Sabella, A. De Domenico, E. Katranaras, M. A. Imran, M. Di Girolamo, U. Salim, M. Lalam, K. Samdanis, and A. Maeder, "Energy efficiency benefits of ran-as-a-service concept for a cloud-based 5g mobile network infrastructure," *IEEE Access*, vol. 2, pp. 1586–1597, 2014.