Energy Efficiency Enhancement on Cloud and Edge Processing by Dynamic RRH Selection

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Abstract—In this paper, for cloud-radio access network (C-RAN) architecture which consists of the cloud and base stations (BSs) via dedicated fronthaul link, we investigate the energy efficiency for cloud processing at the cloud and edge processing at each BS. For cloud processing, we reflect the outdated channel state information (CSI) and additional power consumption for the centralized processing. For edge processing, each RRH is allowed to perform baseband processing based on local, but timely CSI. Thus, we reflect the degradation of spectral efficiency induced by inter-cell interference to our energy efficiency model. Furthermore, we propose an RRH selection algorithm for cloud and edge processing to enhance the energy efficiency. Simulation results show that there certainly exists the regime that the edge processing outperforms than the cloud processing. Moreover, we observe that, by means of our proposed algorithm, the energy efficiency is enhanced, especially in cloud processing.

Index Terms—C-RAN, energy efficiency, RRH selection, cloud processing, edge processing

I. INTRODUCTION

The architecture of fifth generation (5G) networks, in order to cope with various and fast-changing mobile traffic, is envisaged to be characterized by wireless edge segment and the cloud connected to the base stations (BSs) via fronthaul link. This architecture also can be regarded as the extension of cloud-radio access network (C-RAN) which consists of the physically separated central unit (CU) and the remote radio head (RRH) through fronthaul link [1]-[3]. Recently, since this fronthaul link typically entails capacity and latency limitations, many researches have been carried out on optimal functional allocation between the cloud processing at CU and local processing at BSs at the edge for given network functions [4]-[6].

In the meantime, as the scale of communication networks grows, the power consumption on total networks significantly limits the performance of networks [7]. For example, in internet-of-things (IoT) networks as promising future network architecture, power consumption on BSs and devices is very important issue which has to be solved. In addition, due to operation via fronthaul and increase of devices to support, the issue of power consumption becomes more important in C-RAN as well.

In this regard, there are many researches which have studied on the energy efficiency of C-RAN architecture [8]-[12]. In [8], the energy efficiency of C-RAN is investigated with respect to compression and data sharing strategy. The allocation algorithm based on graph partitioning and rejoining for base band unit (BBU) and RRH to minimize power consumption of BBU pool is proposed in [9]. For massive multiple-input multiple-output (MIMO) C-RAN, the heuristic user association algorithms are considered in [10] from energy efficiency viewpoint. In [11], the maximum energy efficiency of cell-free massive MIMO model is studied by solving optimization problem which control the access point (AP) power. Moreover, two different precoding processes of C-RAN are promoted in [12] which can be applied to partially centralized C-RAN. To the best of authors’ knowledge, a study on the analysis of energy efficiency considering the system characteristics of each precoding process explained above is not investigated. Therefore, we are motivated to study an energy efficiency of C-RAN, and propose the method to improve the energy efficiency by using RRH selection.

In this paper, we investigate the energy efficiency in downlink C-RAN system with cloud processing and edge processing. In cloud processing, the cloud is able to produce a precoder in centralized manner using collected, but delayed channel state information (CSI). The delay is caused by the two-way transmission via fronthaul link. On the other hand, in edge processing, each RRH generates a precoder only based on local, but timely CSI. Furthermore, in order to enhance the energy efficiency for each processing, we propose an RRH selection algorithm. The contributions of this paper are as follows:

• We analyze the energy efficiency in downlink C-RAN architecture with cloud processing and edge processing. To elaborate, for cloud processing, we reflect the outdated CSI and addition power consumption due to presence of fronthaul link as trade-off for the processing in centralized manner. For edge processing, since it exploits local, but timely CSI, we reflect the degradation of spectral efficiency induced by inter-cell interference to our energy efficiency model.

• We propose a dynamic RRH selection algorithm to enhance the total energy efficiency. As determining which RRH needs to be switched off in energy efficiency perspective, we guarantee certain level of energy efficiency, while we still support downlink users as many as we can.

The remainder of this paper is organized as follows. The system model is introduced in Section II. In Section III, we address the power consumption model, and we introduce our energy efficiency model for cloud and edge processing. We
present our proposed scheme in Section IV. Simulation results are shown in Section V and we conclude our paper in Section VI.

Notation: Boldface lower case and upper case letters denote column vector and matrix, respectively. The subscript \((\cdot)\) and \((\cdot)^T\) denote conjugate and transpose, respectively. The expectation operation is denoted by \(E[\cdot]\). The notation \(|\cdot|\) stand for absolute value of scalar variable or cardinality of the set, and \(\|\cdot\|\) means the Euclidean norm of a vector. Finally, \(x \sim \mathcal{CN}(\mu, \sigma^2)\) defines a circularly symmetric complex Gaussian random variable \(x\) with mean value \(\mu\) and variance \(\sigma^2\).

II. SYSTEM MODEL

We consider a downlink transmission system model, which consists of one CU, \(M\) RRHs, and \(K\) users. The set of RRHs and users are denoted as \(\mathcal{M} = \{1, \ldots, M\}\), and \(\mathcal{K} = \{1, \ldots, K\}\), respectively. All the RRHs are equipped with \(N \geq 1\) antennas while each user is equipped with single antenna. We assume that the CU is connected to each RRH via wired fronthaul link. In this paper, we don’t consider limited fronthaul link capacity since it is beyond the scope of this paper. For the wireless access link between \(M\) RRHs and the \(K\) users, we assume quasi-static flat fading channels over the same bandwidth \(B\) Hz. The downlink channel between the RRH \(m\) and the user \(k\) is denoted by \(h_{mk}^k = \beta_{mk}^k h_m^k\), where \(\beta_{mk}^k\) is a large scale fading, and \(h_m^k \in \mathbb{C}^{N \times 1}\) is a small scale fading vector. We assume that each element of \(h_m^k\) follows independent and identically distributed (i.i.d.) \(\mathcal{CN}(0, 1)\). As shown in Fig. 1, we consider two downlink signal processing: (1) process at the CU in centralized manner (cloud processing), (2) process at each RRH in distributed manner (edge processing). In the following subsection, we describe each system model in detail. Downlink channel state information (CSI) is obtained based on uplink pilot by means of the property of channel reciprocity \([13]\). Here, we assume perfect channel estimation for simplicity.

A. Signal Model for Cloud Processing

Here, the CU performs centralized process after collecting CSI from each RRH. Specifically, the CU generates precoder in centralized fashion to mitigate all inter-user interference using outdated CSI caused by delay over fronthaul links. Based on \([14]\), we define the outdated CSI, \(\bar{g}_m^k\), as,

\[
\bar{g}_m^k = \lambda g_m^k + \sqrt{1-\lambda^2} f_m^k,
\]

(1)

where \(f_m^k \in \mathbb{C}^{N \times 1}\) are i.i.d \(\mathcal{CN}(0, \beta_m^k)\) random variables. Moreover, \(\lambda\) is the correlation coefficient between \(g_m^k\) and \(\bar{g}_m^k\), which is expressed as \([15]\).

\[
\lambda = J_0(2\pi f_{d,mk} T_{d,m}),
\]

(2)

where \(J_0(\cdot)\) is the zeroth order Bessel function, \(f_{d,mk}\) is the maximum Doppler frequency of the channel between the RRH \(m\) and the user \(k\), and \(T_d\) is the fronthaul delay of the RRH \(m\).

Based on outdated CSI in (1), the CU transmit symbols produced by multiplication of a precoder and data symbols. Let \(q_k\) is the symbol intended to the user \(k\), and \(\mathcal{A}_R\) be the set of active RRHs. Thus, the transmitted symbols from the CU is expressed as,

\[
x = \sqrt{\xi} W q_k.
\]

(3)

Here, \(q_k \triangleq [q_1, q_2, \ldots, q_K]^T \in \mathbb{C}^{K \times 1}\) is the vector of the symbol for all users with \(E[|q_k|^2] = 1\) for \(\forall k\), \(W \in \mathbb{C}^{|\mathcal{A}_R| \times N \times K}\) is a precoder matrix, and \(\xi\) is a normalization factor to satisfy power constraint \(E[|x|^2] = 1\). In this paper, in order to null inter-user interference, we exploit zero-forcing (ZF) precoder, \(W = G^\dagger (G^T G)^{-1}\), where \(G = [g_1  g_2 \cdots  g_K]\) and \(g_k = (g^k_{1T} g^k_{2T} \cdots  g^k_{|\mathcal{A}_R|T})^T\) denote the downlink channel of all users and user \(k\).

Then the received signal of user \(k\) is given by,

\[
y_k = \sqrt{\rho_d} (\bar{g}_k^T) x + z_k
\]

\[= \sqrt{\rho_d \xi} (\bar{g}_k^T) W^k q_k + \sqrt{\rho_d \xi} \sum_{j \neq k} (\bar{g}_j^T) W^j q_j + z_k,
\]

(4)

where \(\rho_d\), \(w^k\), and \(z_k \sim \mathcal{CN}(0, 1)\) denote normalized downlink transmit power, \(k\)-th column of \(W\), and additive Gaussian noise, respectively.

B. Signal Model for Edge Processing

Here, each RRH performs downlink process based on local, but timely CSI. The user candidates set is predefined based on large-scale fading gain \([16]\). We define \(\mathcal{U}_m\) and \(m_k\) as the set of user candidates of the RRH \(m\) and corresponding RRH for user \(k\), respectively. Each RRH generates ZF precoder by using local, but timely CSI. The transmit signal from RRH \(m\) is given as,

\[
x_m = \sqrt{\xi_m} \bar{W}_m q_m,
\]

(5)

where \(q_m \triangleq [q_{m,1} q_{m,2} \cdots q_{m,|\mathcal{U}_m|}]^T \in \mathbb{C}^{|\mathcal{U}_m| \times 1}\) is the vector of the symbol for users who are served by RRH \(m\) with \(E[|q_{m,k}|^2] = 1\) for \(\forall k \in \mathcal{U}_m\), \(\bar{W}_m \in \mathbb{C}^{N \times |\mathcal{U}_m|}\) is the precoder matrix produced by RRH \(m\), and \(\xi_m\) is a normalization.
factor to meet the condition $E[||x_m||^2] = 1$. Contrary to cloud processing, the precoder of each RRH cannot mitigate interference induced by adjacent RRH, since such precoder is generated on the basis of local CSI. However, as the advantage of edge processing, RRH can exploit timely CSI. Thus, the received signal of user $k$ at RRH $m_k$ is given by

$$y_k = \sqrt{\rho_d} \sum_{m \in A_R} (g_{km}^k)^T x_m + z_k$$

$$= \sqrt{\rho_d} \sum_{m \in A_R \setminus \{m_k\}} (g_{km}^k)^T W_{mk} q_{mk} + \sqrt{\rho_d} \sum_{m \in A_R \setminus \{m_k\}} \sqrt{\xi_m} (g_{km}^k)^T W_{mk} q_{mk} + z_k$$

$$= \sqrt{\rho_d} \sum_{m \in A_R \setminus \{m_k\}} (g_{km}^k)^T w_{mk} q_k + \sqrt{\rho_d} \sum_{m \in A_R \setminus \{m_k\}} \sqrt{\xi_m} (g_{km}^k)^T w_{mk} q_{mk} + z_k + \sqrt{\rho_d} \sum_{m \in A_R \setminus \{m_k\}} \sqrt{\xi_m} (g_{km}^k)^T w_{mk} q_j + z_k,$$ (6)

where $w_{mk}^k$ is a $k$-th column of $W_m$ and $A_R$ is a set of activated RRHs.

### III. Analysis on Energy Efficiency

In this section, we address the power consumption model, and define the energy efficiency for cloud processing and edge processing. We consider all power consumption on system components such as CU, RRHs, fronthaul links, and users. In C-RAN, the power consumption related to RRH $m$ for the signal transmission procedure is modeled as follows [12], [17]-[18],

$$P_m = P_{m}^{f,u} + P_m^c + P_m^{f,d},$$ (7)

where $P_m^{f,u}$ is the power consumed by the fronthaul link of RRH $m$ due to transmit the CSI to the CU. $P_m^c$ denotes circuit power consumption at RRH $m$ such as amplifier, and $P_m^{f,d}$ implies the power consumption on fronthaul link of RRH $m$ caused by downlink transmission. Specifically, $P_m^{f,u}$ is given by,

$$P_m^{f,u} = P_{fix,m} + \alpha N K b_Q f_{pre} P_{dm,m},$$ (8)

where $P_{fix,m}$ is a traffic-independent fixed power consumption of $m$-th fronthaul, $\alpha$ is the redundancy in the fronthaul transport interface, $b_Q$ is the number of IQ samples bits, $f_{pre}$ is the frequency of updating the precoder, and $P_{dm,m}$ is the traffic-dependent power in W/bps. The RRH power consumption $P_m^c$ is expressed as,

$$P_m^c = \frac{1}{\alpha_m} \rho_d N_0 + N P_{e,m},$$ (9)

where $\alpha_m$ is the efficiency of power amplifier, $N_0$ is the noise power, and $P_{e,m}$ is the power to run the internal circuit components of each RRH antenna. In a similar manner of $P_m^{f,u}$, $P_m^{f,d}$ is expressed as,

$$P_m^{f,d} = P_{fix,m} + BS e_P_{dm,m}.$$ (10)

Eq. (10) is followed by substituting the total sum-rate of the system for the precoder rate in $P_m^{f,u}$.

Here, we define the total energy efficiency of the system for cloud and edge processing. First, the spectral efficiency is defined equally for both cloud and edge processing as

$$S_e = \sum_{k=1}^{K} \log_2(1 + \gamma_k^l),$$ (11)

where $l \in \{C, E\}$ and $\gamma_k$ denotes the received signal-to-interference-plus-noise-ratio (SINR) of user $k$. The SINR of user $k$ is given by (12) and (13) for cloud and edge processing, respectively. For edge processing, unlike (12), there exists the inter-cell interference since each RRH produces a precoder only based on local CSI.

The power consumption for cloud processing is threefold. First, in order to send CSI from each RRH to CU, the power defined as $P_{m}^{f,u}$ is consumed via fronthaul link. Next, after the CU produces a precoder and multiply it by all user’s symbols, the power $P_m^{f,d}$ is consumed for downlink transmission via fronthaul link. Last, each RRH requires certain power $P_m^c$ to operate circuit to service its downlink users. In this paper, the power consumption for operating CU, which can be regarded as constant is neglected for simplicity. For edge processing, we only consider circuit power consumption on each RRH, since it doesn’t need CU. Therefore, the power consumption for cloud and edge processing is given by,

$$P^C_t = \sum_{m \in A_R} (P_m^{f,u} + P_m^c + P_m^{f,d}),$$ (14)

$$P^E_t = \sum_{m \in A_R} P_m^c.$$ (15)

Finally, the total energy efficiency for both processing is expressed as,

$$\eta_l = \frac{BS e_l}{P^l_t}, \text{ for } l \in \{C, E\}$$ (16)

### IV. Dynamic RRH Selection for Energy Efficiency Enhancement

In this section, we present our proposed algorithm for dynamic RRH selection to enhance total energy efficiency considering two different scenarios, cloud processing and edge processing. To elaborate, in the viewpoint of enhancing spectral efficiency, supporting downlink users as many as we can by switching on all RRHs seems to be effective, while the total power consumption increases which may result in degradation of the total energy efficiency after all. Thus, in the following subsections, we describe how to properly select RRHs in two different scenarios.

#### A. Cloud Processing

Here, the CU selects the set of RRHs in centralized manner by following our proposed algorithm described in Algorithm 1. Specifically, the CU exploits all collected CSI to determine which RRHs should be switched on. In our proposed algorithm, first, we need to determine $MN$ number of user candidates, since at most the number of users same as the number of total transmit antennas can be supported...
with CSI. In our algorithm, we exploit the maximum number of determinates whether switch off itself based on local, but timely B. Edge Processing algorithm ends.

there is no more non-zero \( \eta \) simultaneously. Here, as described in Algorithm 1, we filter our algorithm, we assume that criterion for RRH selection [10]. Before each RRH performs of \( c_m \), most likely inefficient RRH is checked first. When there is more non-zero \( c_m \) which implies that the RRH \( m \) with \( c_m = 0 \) doesn’t have any associated users to serve, our algorithm ends.

B. Edge Processing

Contrary to cloud processing, in edge processing, each RRH determines whether switch off itself based on local, but timely CSI. In our algorithm, we exploit the maximum number of users, cardinality of \( U_m \), to which each BS can afford as criterion for RRH selection [10]. Before each RRH performs our algorithm, we assume that \( U_m \) is pre-determined based on the large-scale fading gain for each RRH. In other words, each user is supported by the closed RRH. With certain predefined threshold \( k_{th} \), each RRH decides to switch off, if \( |U_m| < k_{th} \). This implies that the RRH that serves the less users is likely to be not useful to enhance the total energy efficiency. Then, we calculate the total energy efficiency. In Algorithm 2, we summarize our algorithm for edge processing.

V. SIMULATION RESULTS

In this section, we evaluate the performance of energy efficiency for cloud and edge processing by adopting the RRH selection algorithm. We consider a 1×1km² region network, and all of the RRHs and the users are uniformly distributed. The transmission bandwidth of the downlink access link is \( B = 20\text{MHz} \). We assume that the path loss model with Rayleigh fading for the downlink channel, and the large scale fading factor is modeled as \( d_m^{k} = -128.1 - 37.6 \log_{10}(d_m^{k}) \) in dB, where \( d_m^{k} \) is the distance between the RRH \( m \) and the user \( k \). The thermal noise density is \( N_0 = -174\text{dBm/Hz} \). Moreover, the parameters of power consumption model are given in Table I. These values are taken from [11], [12].

\[
\gamma^C_k = \frac{\rho d_k \xi}{\rho d_k \sum_{j \neq k} |(g^k_j)^T w^j|^2 + 1},
\]

\[
\gamma^E_k = \frac{\rho d_k \xi_{m_k}}{\rho d_k \sum_{j \in U_{m_k} \setminus \{k\}} |(g^k_{m_k})^T w^j|^2 + \rho d \sum_{m \in A_R \setminus \{m_k\}} \xi_k \sum_{j \in U_m} |(g^k_m)^T w^j|^2 + 1}.
\]

Algorithm 1 Dynamic RRH selection with cloud processing

1: Initialization: \( A_R = M, \ U = \emptyset \)
2: if \( K > MN \) then
3: \quad while \( |U| > MN \) do
4: \qquad \tilde{k} = \text{argmin}_{k \in \mathcal{U}} \| g^k \|, \ \ U = \mathcal{U} \setminus \{ \tilde{k} \}.
5: \quad end while
6: end if
7: Calculate the energy efficiency \( \eta^C_k \) using (16) with \( A_R \) and \( \mathcal{U} \).
8: for \( \forall m \in A_R \) do
9: \quad \tilde{m} = \text{argmin}_{m \in A_R \setminus \{ m_k \}} \| g^m \|, \ \ \tilde{A}_R = A_R \setminus \{ \tilde{m} \}.
10: end for
11: \( n = 1. \)
12: while \( \max_{m \in A_R} c_m > 0 \) do
13: \quad \tilde{m} = \text{argmin}_{m \in A_R \setminus \{ m_k \}} \| g^m \|, \ \ \tilde{A}_R = A_R \setminus \{ \tilde{m} \}.
14: \quad U = \tilde{A}_R.
15: \quad while \( |U| > |\tilde{A}_R|N \) do
16: \qquad \tilde{k} = \text{argmin}_{k \in \mathcal{U}} \| g^k \|, \ \ \tilde{U} = \mathcal{U} \setminus \{ \tilde{k} \}.
17: \quad end while
18: Calculate the new energy efficiency \( \eta^C_m \) using (16) with \( \tilde{A}_R \) and \( \tilde{U} \).
19: if \( \eta^C_m > \eta^C_{m-1} \) then
20: \quad \tilde{A}_R = \tilde{A}_R.
21: end if
22: \( c_{\tilde{m}} = 0, \ n = n + 1 \)
23: end while

In Fig. 2, we compare the energy efficiency of cloud and edge processing with respect to the channel correlation coefficient \( \lambda \) with \( M = 3, N = 5 \), and \( K = 30 \). Followed by (1), if \( \lambda \) is equal to 1, channel doesn’t become outdated after the delay over fronthaul link. For edge processing, we assume the threshold \( k_{th} = 2 \) for our algorithm. It is shown that energy efficiency of cloud processing becomes worse than those of edge processing in low regime of \( \lambda \), since the collected CSI at the cloud becomes more outdated. To elaborate, due to outdated CSI, the precoder generated at the cloud is not able to mitigate inter-user interference well, thus the spectral efficiency of cloud processing decreases. Since the edge processing doesn’t use fronthaul link, the energy efficiency of those is irrelevant to \( \lambda \). In addition, we observe
Algorithm 2 Dynamic RRH selection with edge processing

1: Initialization: $\mathcal{U}_m = \phi$ for $\forall m \in \mathcal{M}$, $\mathcal{A}_R = \phi$.
2: for $\forall k \in \mathcal{K}$ do
3: $\tilde{m} = \arg\max_{m \in \mathcal{A}_m} \beta_{m,k}^k$, $\mathcal{U}_{\tilde{m}} = \mathcal{U}_{\tilde{m}} \cup \{k\}$.
4: end for
5: for $\forall m \in \mathcal{A}_R$ do
6: while $|\mathcal{U}_m| > N$ do
7: $\tilde{k} = \arg\min_{k \in \mathcal{U}_m} \beta_{m,k}^k$, $\mathcal{U}_m = \mathcal{U}_m \setminus \{\tilde{k}\}$.
8: end while
9: if $|\mathcal{U}_m| < k_{th}$ then
10: $\mathcal{A}_R = \mathcal{A}_R \setminus \{m\}$
11: end if
12: end for
13: Calculate the energy efficiency $\eta^E$ using (16) with updated $\mathcal{A}_R$ and $\mathcal{U}_m$ for $\forall m \in \mathcal{A}_R$.

TABLE I: Parameters of power consumption model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{d_{x,m}}$</td>
<td>0.825 W</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>4/3</td>
</tr>
<tr>
<td>$b_{IQ}$</td>
<td>20</td>
</tr>
<tr>
<td>$f_{pre}$</td>
<td>1.5 MHz</td>
</tr>
<tr>
<td>$P_{d_{id,m}}$</td>
<td>0.25 W/Gbps</td>
</tr>
<tr>
<td>$\alpha_{m}$</td>
<td>0.4</td>
</tr>
<tr>
<td>$P_{ic,m}$</td>
<td>0.2 W</td>
</tr>
<tr>
<td>$\rho_{d}N_0$</td>
<td>1 W</td>
</tr>
</tbody>
</table>

that the energy efficiency of both processing is enhanced by RRH selection (solid line in Fig. 2). It is seen that, by means of our proposed algorithm, the network save the power consumption while certain level of spectral efficiency is still obtained. The reason why the cloud processing has more enhancement by the RRH selection is the power consumption related to each RRH entails the power consumed on fronthaul link as well. In other words, if a RRH is decided to be switched off, we can save more power in cloud processing than those of edge processing.

In Fig. 3, we observe the sum spectral efficiency of cloud and edge processing under same environment in Fig. 2. Unlike the Fig. 2, the sum spectral efficiency of cloud processing without RRH selection has the largest value when $\lambda = 1$, since the ZF precoder generated by the cloud with perfect CSI is able to mitigate all inter-user interference. In other words, in the viewpoint of sum spectral efficiency, it is the best to support downlink user as many as we can by switching on all available RRHs. However, after applying RRH selection algorithm, it is shown that the sum spectral efficiency increases at the low regime of $\lambda$ in cloud processing. This implies that when the CSI is outdated whereby the precoder cannot perfectly eliminate inter-user interference, it is better to properly select RRH and the number of users to support. However, for edge processing, the enhancement of sum spectral efficiency is little, since our algorithm doesn’t focus on leveraging inter-cell interference. This little enhancement is just caused by decrease of inter-cell interference induced by idle RRH.

In Fig. 4, we evaluate the energy efficiency of cloud and edge processing with respect to threshold $k_{th}$, which is the criterion of our proposed algorithm for deciding whether switch off such RRH. It is seen that the energy efficiency after RRH selection in edge processing behaves as “rise-and-drop”. This is because, as $k_{th}$ becomes larger, the number of idle RRHs increases, and, accordingly, the network saves more
power consumption. In this regard, inter-cell interference also disappears due to idle RRHs as well. However, if $k_{th}$ becomes too large, it is hard to find RRHs which satisfies this condition. Accordingly, since most of RRH goes to idle mode, the energy efficiency decreases in edge processing. Therefore, it is seen that there exists an optimal threshold $k_{th}$ for our proposed algorithm of edge processing.

VI. CONCLUSIONS

In this paper, we investigated the energy efficiency of cloud and edge processing in downlink C-RAN architecture. For the cloud processing, due to fronthaul link, outdated CSI and addition power consumption was considered as trade-off for centralized processing at the cloud. In contrast, for the edge processing, each RRH was allowed to perform baseband processing based on local, but timely CSI. Furthermore, we proposed a dynamic RRH selection algorithm for cloud and edge processing, respectively, to enhance the total energy efficiency. In simulation results, we observed that the energy efficiency of edge processing outperforms when the delay over fronthaul becomes worse. In addition, it is shown that our proposed algorithm can improve the energy efficiency for both processing by properly selecting RRHs.

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