RRH Clustering in Cloud Radio Access Networks

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***Abstract*—Cloud Radio Access Network (C-RAN) offers an evolution in base stations architecture. The base station is broken down into a Base Band Unit (BBU) and a Remote Radio Head (RRH). While BBUs are pooled in a single geographical point, RRHs are distributed across multiple sites. In conventional architectures, a one-to-one logical mapping exists between BBUs and RRHs. One BBU is assigned to one RRH, so as to maximize network capacity. However, in the C-RAN architecture, a one-to-many logical mapping may be established. One BBU is assigned to many RRHs, so as to reduce network power consumption. In this paper, we investigate the BBU-RRH mapping, also known as the RRH clustering problem, and formulate it as a bin packing problem. Optimal and heuristic solutions are derived to reduce network power consumption, without compromising user quality of service. Simulation results illustrate the benefits from clustering RRHs, and prove that our heuristic achieves close performance to the optimal solution.**

***Index Terms*—Cloud radio access network, energy efficiency, RRH clustering, bin packing problem.**

I. INTRODUCTION

Over the past few years, the demand for mobile traffic has steadily increased. So as to provide acceptable quality of service (QoS), telecom operators densify their access networks. This however leads to many challenges:

- *Power consumption increase*: Deploying more base stations (BS) increases network power consumption. This has tremendous impact on operational expenditures and environment [1].
- *Low base station utilization efficiency*: The mobile traffic is on a dynamic move. At some time of the day, some BSs are oversubscribed, while others are in idle mode. Consequently, radio resources are inefficiently utilized.

Centralized or Cloud Radio Access Network (C-RAN) is the answer to the above challenges. The C-RAN architecture aggregates all BBUs – intelligent elements that handle the base band functionalities of the signal – in one cloud. The RRHs – lighter elements that modulate and amplify the signal – are distributed across multiple sites. As a consequence, the C-RAN architecture introduces centralized, flexible, and more intelligent management. Lower power consumption and efficient resource utilization can be achieved [1].

Conventional architectures are based on the logical one-to-one mapping (1:1), so that one BBU is assigned to only one RRH. Radio resources may be consequently underused: one RRH may not consume all of the BBU radio resources. However, the C-RAN architecture changes this concept, and the static mapping between BBUs and RRHs no longer exists. One BBU may be assigned to many RRHs, so that the number of simultaneously active BBUs is reduced. Typically as a function of network load conditions, a one-to-many logical mapping (1:N) may be established: N RRHs share the resources of one single BBU, enhancing network energy efficiency [2].

II. RELATED WORK

RRH clustering has been proposed, in the literature, for many purposes. In [3], the authors propose a dynamic clustering to introduce multi-cell cooperation (*i.e.,* Coordinated Multi-Point (CoMP) transmission). RRHs, that are assigned to one single BBU, simultaneously transmit the same signal. This maximizes the system utility. In [2], the authors introduce clustering to maximize user satisfaction. Signaling load is reduced, without compromising user QoS. They also enhance network energy efficiency, expressed through the number of active BBUs. However, in our work, we do not only consider the number of active BBUs, but also adopt a power consumption model (cf. section III) to closely examine the impact of clustering on network energy efficiency. In [4], the authors propose a dynamic bandwidth allocation. They dynamically change the BBU-RRH mapping, only when non-overlapping bandwidths are allocated to neighboring RRHs. The proposed solution has a direct impact on network energy efficiency. However, we believe that through other methods and optimal algorithms, network energy efficiency could be even more enhanced, and radio resources better exploited.

This paper aims to study the RRH clustering, also known as the BBU-RRH mapping, in order to enhance radio resource utilization and power consumption. We provide the same level of QoS, expressed as numbers of required resource blocks (RBs) in available RRHs, as in a one-to-one mapping scenario.

Limiting the number of active BBUs reduces network power consumption and enhances radio resource utilization. However, this should not compromise user QoS. We formulate, in section III, the BBU-RRH mapping as a *modified bin packing* problem. Two main constraints are considered: first, radio resources of each active BBU must be enough to meet the demands of its mapped RRHs. Second, cells (*i.e.,* RRHs) that are assigned to a single BBU should be contiguous, or equivalently geographically adjacent. For instance, if we consider different cells of hexagonal form, an hexagon must share at least one common border with another one belonging to the same BBU.

We obtain optimal solutions through dynamic programming [5]. Yet, and since the bin packing problem is known to be NP-hard [6], optimal solutions are hard to derive in large networks.

We therefore propose a heuristic algorithm to cluster RRHs, and prove its efficiency for implementation in practice.

The rest of the paper is organized as follows: Section III formulates the BBU-RRH mapping as a bin packing problem. Section IV introduces optimal solutions, while section V describes our heuristic algorithm. Performance evaluation is presented in section VI. Section VII concludes the paper.

III. Problem Formulation

In bin packing problems, objects of different volumes are packed into a finite number of bins or containers. Each bin has a volume V [7]. The objective is however to minimize the number of used bins.

In our work, we formulate the BBU-RRH mapping as a one dimensional bin packing problem. The objects are the RRHs with different average RB demands, and the BBUs are the containers with a maximum volume or capacity of C RBs. Subject to the BBU maximum capacity and to the geographical adjacency constraints, the BBU-RRH mapping must be done in a way to reduce the number of active BBUs, while providing the same level of QoS as in the case of a one-to-one mapping.

A. Bin Packing Formulation

We consider a BBU B of capacity C and a set of n RRHs $r_1, ...r_n$, each with an average RB demand $d_1, ..., d_n$. A neighbor relation, namely $n_{kl} = 1$, exists between r_k and r_l when they are geographically adjacent. However, when they share no border, $n_{kl} = 0$.

The problem consists of finding a number of BBUs $S \leq n$ and an S-partition $Cl_1 \cup .... \cup Cl_S$ of the set $\{1, ..., n\}$ such that $\sum_{i \in Cl_k} d_i \leq C$ for all $k = 1, ..., S$. A solution is optimal when it has minimal S. The Integer linear programming formulation of the problem is:

$$\textit{Minimize } S = \sum_{i=1}^{n} y_i$$

Subject to:

$$\sum_{j=1}^{n} d_j x_{ij} \leq C y_i, \forall i \in \{1, ..., n\} \tag{1}$$

$$\sum_{i=1}^{n} x_{ij} = 1, \forall j \in \{1, ..., n\} \tag{2}$$

$$\sum_{\substack{l=1 \\ l \neq j}}^{n} z_{ijl}.n_{jl} \geq \min(1, \sum_{\substack{l=1 \\ l \neq j}}^{n} z_{ijl}), \forall i \in \{1, ..., n\}, \quad \forall j \in \{1, ..., n\} \tag{3}$$

$$y_i \in \{0, 1\}, \forall i \in \{1, ..., n\} \tag{4}$$

$$x_{ij} \in \{0, 1\}, \forall i \in \{1, ..., n\}, \forall j \in \{1, ..., n\} \tag{5}$$

$$z_{ijl} \leq x_{ij}, \forall i \in \{1, ..., n\}, \forall j \in \{1, ..., n\}, \forall l \in \{1, ..., n\} \tag{6}$$

$$z_{ijl} \leq x_{il}, \forall i \in \{1, ..., n\}, \forall j \in \{1, ..., n\}, \forall l \in \{1, ..., n\} \tag{7}$$

$$z_{ijl} \geq x_{ij} + x_{il} - 1, \forall i \in \{1, ..., n\}, \forall j \in \{1, ..., n\}, \forall l \in \{1, ..., n\} \tag{8}$$

where $y_i = 1$ if BBU i is used, $x_{ij} = 1$ if r_j is associated to BBU i, and $z_{ijl} = 1$ if r_j and r_l are both associated to BBU i.

Inequality (1) expresses the BBU maximum capacity constraint, while inequality (3) expresses the geographical adjacency constraint.

B. Power Consumption Model

The power a BBU consumes is a linear function of the data transmission rate [8]. It also depends on the number of used CPU cores and their speed, considered constant and denoted by α in our work. Thus, the power consumed by an active BBU is as follows:

$$P_B = \alpha + \beta r \tag{9}$$

where:

- P_B: The power consumed by an active BBU
- α: The minimum power consumption of an active BBU at 0 load
- β: The variation coefficient of P_B as a function of r
- r: The data transmission rate

IV. Optimal solution

To derive an optimal solution, a dynamic programming is used. The bin packing problem is thereby divided into sub-problems. Each sub-problem has its own local optimal solution [5]. The best among all is adopted. Our algorithm starts by finding all of the feasible partitions, where the cluster size is limited to 2. Thus, a first solution space is built. Then, it continues to search for all the possibilities where the cluster size is limited to 3. A second solution space is built and added to the first one.

For clusters of size n, the algorithm tries to identify possible combinations of size $n-1$, $n-2$, ... , $n-(n-1)$.

For illustration, in figure 1, if we consider that the BBU capacity is limited to 25 RBs, and given the average RB demand in serving RRHs, some of the feasible partitions the optimal algorithm generates are:
$\{[D, F, G]; [A, H]; B; C\}$ or $\{[B, H, G]; [A, F]; C; D\}$.

After generating all feasible combinations, the adopted power consumption model is applied. Each built solution space has its own selected combinations that minimize network power consumption. After generating all sub-optimal combinations for each solution space, the ones that minimize the

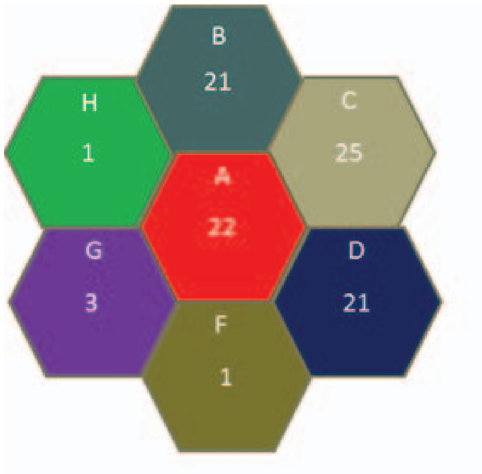

Fig. 1. Set of cells

number of active BBUs are chosen. The optimal algorithm is summarized in figure 2.

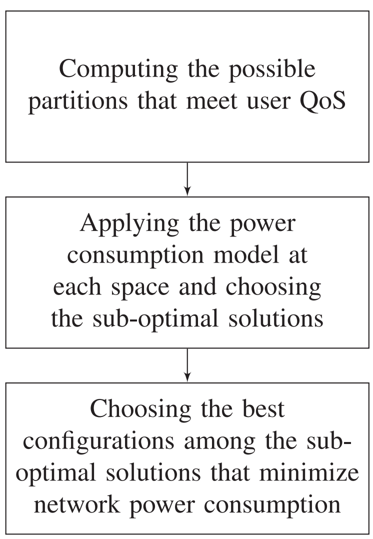

Fig. 2. Flowchart of the optimal solution

Usually, exact methods of NP-hard problems have a time complexity of $O(2^n)$ [9]. In the following section, we describe our heuristic algorithm, inspired from two existing bin packing heuristics that reduce the problem complexity to $O(n)$ in worst case [10].

V. Heuristic Solution

Inspired from the Best Fit Decreasing (BFD) and the Worst Fit Decreasing (WFD) strategies [6], we propose a heuristic algorithm that tries to fill all unused gaps, in a way to make the most of the unused RBs. The particularity of our algorithm, in comparison with the BFD and the WFD methods, is that it takes into consideration the geographical adjacency constraint.

Algorithm 1 describes our heuristic method. We denote by $\mathcal{R}$ the set of available RRHs, $\mathcal{D}$ their demands expressed as number of required RBs, and $\mathcal{V}$ the set of all clusters and RRHs that are candidates to be clustered. $\mathcal{V}$ is initialized to $\mathcal{R}$.

Algorithm 1 mainly consists of the following steps:

- Sort the set $\mathcal{D}$ of the demands d_i of all RRHs r_i.
- Choose the cluster or RRH $r_h \in \mathcal{V}$ with the highest demand $d_h \in \mathcal{D}$.
- Form the set of RRHs $r_j \in \mathcal{R}' \subset \mathcal{R}$ of all the neighbors of r_h, as well as all the associated demands $d_j \in \mathcal{D}' \subset \mathcal{D}$.
- The neighbor RRH r_s with the smallest RB demand d_s is chosen to be clustered with r_h, subject to: $d_h + d_s \leq C$, where $d_h + d_s$ is the total demand of both r_h and r_s, and C is the maximum BBU capacity. A new cluster $r_{h\cup s}$ with its associated demand $d_{h\cup s}$ is updated.
- If r_s does not satisfy the inequality $d_h + d_s \leq C$, r_h is no more clustered. The algorithm then repeats with $r_{h'}$ that has the demand $d_{h'}$, that comes straight below d_h. We further update $\mathcal{V}$.

Algorithm 1: Heuristic algorithm

1 Initialize $d_i \in \mathcal{D}$;
2 Attribute $d_i \in \mathcal{D}$ to $r_i \in \mathcal{R}$;
3 Initialize $\mathcal{V} = \mathcal{R}$;
4 **repeat**
5   Sort $d_i \in \mathcal{D}$;
6   Select $d_h = \max_{r_i \in \mathcal{V}} d_i$ and its associated r_h;
7   Form $\mathcal{D}' \subset \mathcal{D}$ and $\mathcal{R}' \subset \mathcal{R} /\ n_{ij} = 1$ where $r_j \in \mathcal{R}'$;
8   Select $d_s = \min_{r_j \in \mathcal{R}'} d_j /\ d_j \in \mathcal{D}'$ and $r_j \in \mathcal{R}'$;
9   **if** $d_h + d_s \leq C$ **then** ;
10     $r_{h\cup s} \leftarrow r_h \cup r_s$;
11     $d_{h\cup s} \leftarrow d_h + d_s$;
12   Update $\mathcal{D}$, $\mathcal{R}$ and $\mathcal{V}$;
13   **else**
14         $\mathcal{V} \leftarrow \mathcal{V} - \{r_h\}$;
15   Select $d_{h'} = \max_{r_i \in \mathcal{V}} d_i$;
16         $r_h \leftarrow r_{h'}$;
17   Go to step 7;
18 **until** $\mathcal{V} = \emptyset$;

The algorithm repeats until no more clustering can be performed, or equivalently until there is no more neighboring RRHs or clusters of total demand less than C.

VI. Simulations and Results

For illustration, we consider a small network made of seven cells. Simulations are run for different load conditions, namely low, medium, and high load conditions. The data transmission rate of 1 RB is calculated according to the LTE standard, and the adopted parameters are listed in table I. Average radio conditions are considered, and 16-QAM modulation is assumed to be used. Simulations are repeated 2000 times. Performance metrics are averaged and shown with 95% confidence interval.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
OFDM symbols per RB	7
Subcarriers per OFDM symbol	12
Bits per subcarriers	4
RB duration	0.5 ms
α	50 W
β	0.6
C	25

A. Load conditions

We consider three integer intervals of uniformly distributed RBs:

- $RB \in [1, 5]$, for low load conditions.
- $RB \in [8, 13]$, for medium load conditions.
- $RB \in [20, 25]$, for high load conditions.

B. Optimal vs. no clustering

We first illustrate the results of the optimal solution in comparison with a one-to-one static mapping, denoted as "no clustering".

As we can see in figure 3, the energy efficiency is shown as a function of average RRH demands. It is defined as the ratio of the total data transmission rate of all RRHs to the total power consumed by all active BBUs according to (9).
At low load conditions, the energy efficiency has a value of almost 0.225 Mb/s/W with clustering, while it has a value less than 0.05 Mb/s/W without clustering. At medium load conditions, the energy efficiency has almost the same value as for low load conditions with clustering, while it is almost at 0.125 Mb/s/W without clustering. At high load conditions, the energy efficiency has the same value of almost 0.25 Mb/s/W with and without clustering. As a conclusion, an improvement value of 77% is achieved to the energy efficiency at low load conditions, while a value of 44% is achieved at medium load conditions.

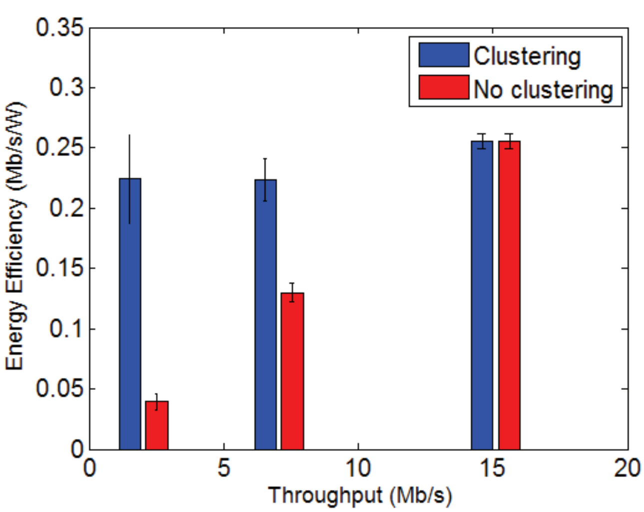

Fig. 3. Energy efficiency: optimal vs. no clustering

Figure 4 displays the utilization efficiency of radio resources as a function of average RRH demands. It is defined as the ratio of the total number of used RBs in all RRHs to the total number of available RBs in active BBUs. At low load conditions, the utilization efficiency of radio resources is almost 80% with clustering, while it is 10% without clustering. At medium load conditions, the utilization efficiency has almost the same value as for low load conditions with clustering, while it is almost at 40% without clustering. At high load conditions, the utilization efficiency is around 90% with and without clustering. We deduce that the utilization efficiency shows an improvement of 70% at low load conditions, while it shows an improvement of 40% at medium load conditions. At high load conditions, the utilization efficiency has the highest level of 90%.

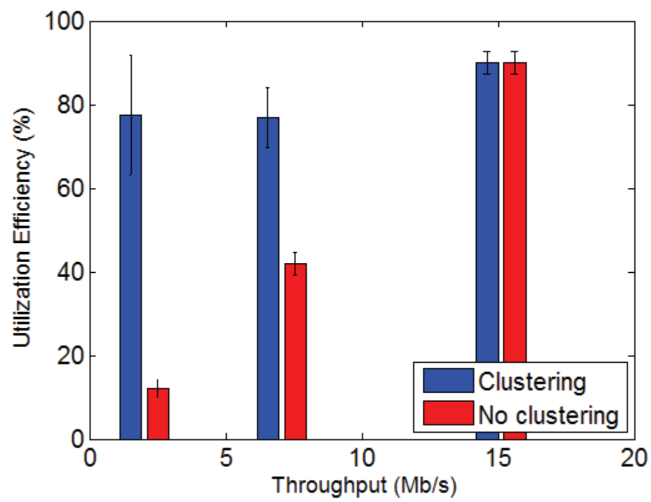

Fig. 4. Utilization efficiency: optimal vs. no clustering

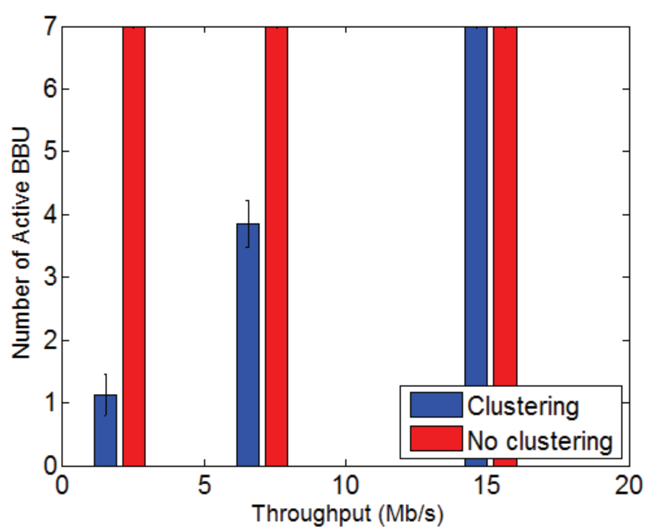

Fig. 5. Number of active BBUs: optimal vs. no clustering

Figure 5 illustrates the mean number of active BBUs as a function of average RRH demands. At low load conditions, the mean number of active BBUs is almost 1 with clustering, while it remains 7 without clustering. At medium load conditions, the mean number of active BBUs is almost 4 with clustering, while it persists on 7 without clustering. At high load conditions, the mean number of active BBUs remains the same with and without clustering. As a conclusion, the clustering has a huge impact on the mean number of active BBUs at low load conditions, while the one-to-one mapping remains the best at high load conditions. Instead of having 7 active BBUs, we can have only 1 at low load conditions and 4 at medium load conditions, thus reducing network power consumption without compromising user QoS.

C. No clustering vs. optimal vs. heuristic

This subsection compares heuristic, optimal and no clustering solutions.

Figure 6 shows the energy efficiency as a function of average RRH demands. At low load conditions, energy efficiencies of optimal and heuristic solutions are the same, while they slightly differs at medium load conditions. At high load conditions, the energy efficiency remains the same for all of the three solutions.

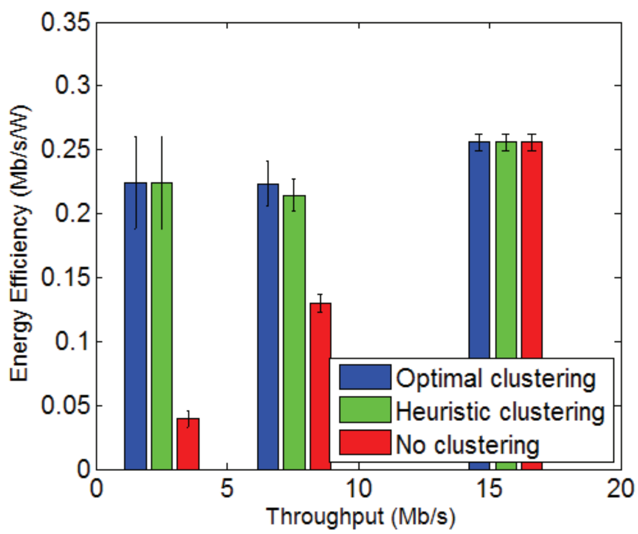

Fig. 6. Energy efficiency: heuristic vs. optimal vs. no clustering

Figure 7 displays the resource utilization efficiency as a function of average RRH demands. At low load conditions, utilization efficiencies of optimal and heuristic solutions are the same, while they slightly differ at medium load conditions. At high load conditions, the results remain the same for all of the three solutions.

Figure 8 illustrates the number of active BBUs as a function of average RRH demands. At low load conditions, the results of the optimal and heuristic clusterings are similar, while at medium load conditions they slightly differ. As a matter of fact, the number of active BBUs is slightly less than 4 for the optimal solution and slightly greater than 4 for the heuristic solution. At high load conditions, the results remain the same, since no clustering can be achieved due to the BBU capacity constraint.

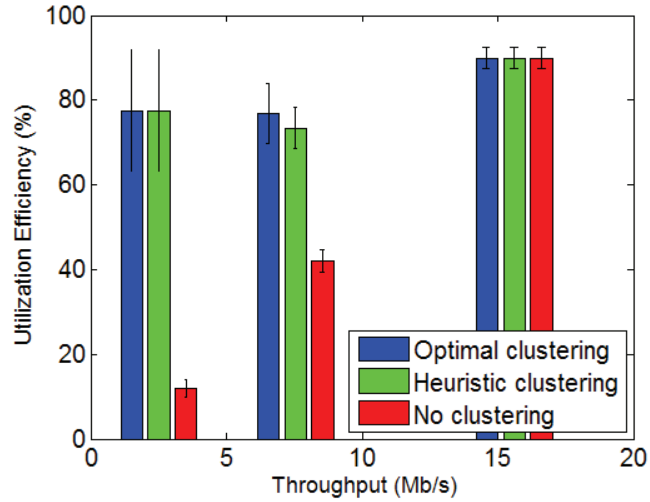

Fig. 7. Utilization efficiency: heuristic vs. optimal vs. no clustering

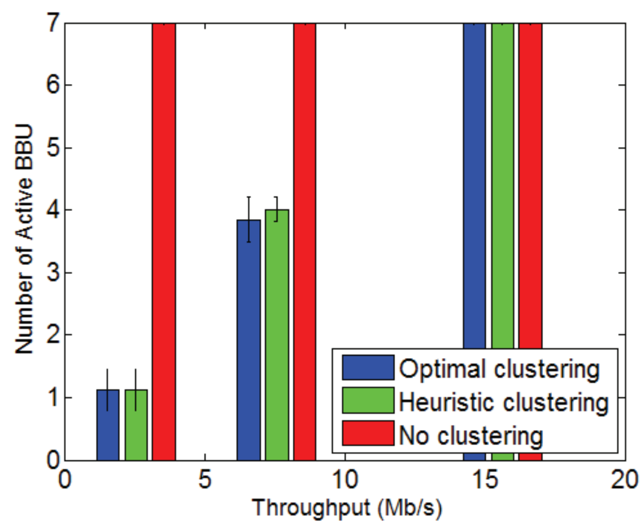

Fig. 8. Number of active BBUs: heuristic vs. optimal vs. no clustering

VII. Conclusion

In this paper, we have formulated the RRH clustering problem in C-RANs as a bin packing problem, and provided optimal and heuristic solutions. Our contribution introduced significant amelioration on energy efficiency and utilization efficiency, at low and medium load conditions, without compromising user QoS. The proposed heuristic provides close performance to the optimal solution, at low and medium load conditions, with less computational complexity. The one-to-one mapping remains the best at high load conditions, due to the BBU capacity constraint. As future work, another problem formulation that compromises user QoS, typically at high load conditions, will be presented.

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