An Efficient Heuristic for Joint User Association and RRH Clustering in Cloud Radio Access Networks

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Abstract*—Cloud Radio Access Network (C-RAN) is a promising mobile network architecture that breaks down the conventional base station into two main parts: the Base Band Unit (BBU) and the Remote Radio Head (RRH). In this context, deciding to which RRH users connect is known as the user association problem. Moreover, RRHs may be mapped to a single BBU, achieving statistical multiplexing gain. Deciding what RRHs are grouped together is known as the RRH clustering problem. As these two problems are mutually dependent, we formulate in this paper the joint user association and RRH clustering problem. Our objective is to maximize the network throughput, while reducing the network power consumption. Since our joint problem is NP-hard, we propose to decompose it into two sub-problems: the user association (UA) sub-problem and the RRH clustering (RC) sub-problem. First, a low-complexity heuristic, based on the received SINR, is used to solve the UA sub-problem. Second, a low-complexity heuristic, based on the merge-and-split rules, is introduced to solve the RC sub-problem. These two sub-problems are sequentially and iteratively solved until convergence is reached. We further evaluate the performance of our proposed solution. Simulation results show that our proposed heuristic solution for the RC sub-problem strikes a good compromise between computational complexity and performance, in comparison with the optimal exhaustive search method. Furthermore, our proposed solution for the RC sub-problem outperforms the no-clustering method, where one BBU is exclusively dedicated to each RRH, and the grand coalition method, where all RRHs are attached to a single BBU.

I. Introduction

5G cellular networks are expected to meet the challenges of the explosive mobile data traffic growth. In this context, Cloud Radio Access Network (C-RAN) was introduced as a promising network architecture, to enhance network performance and reduce network power consumption. The traditional base station is broken down into a Base Band Unit (BBU) and a Remote Radio Head (RRH). While the BBUs are pooled in a cloud data center, the RRHs are distributed across multiple sites. Moreover, the RRHs are connected to the BBUs via high-performance optical fronthaul links. In practice, to cope with the huge demand for capacity, RRHs are densely deployed. Deciding to which RRH users connect is known as the user association problem. Typically, user association decisions depend on user radio conditions and radio resource availabilities. Furthermore, RRHs may be clustered, achieving statistical multiplexing gain. More precisely, RRHs that serve few users are mapped to a single BBU, sharing the same resource pool. This reduces the network power consumption and the total interference level. Deciding what RRHs are grouped together is known as the RRH clustering problem.

The user association and the RRH clustering problems are mutually dependent. On the one hand, RRHs that are grouped together share the same radio resource pool. Moreover, as only one user per BBU is served at a time, they do not create interference on each other. Therefore, the RRH clustering influences user radio conditions and radio resource availabilities, and consequently user association decisions. On the other hand, the user association influences RRH load conditions and consequently clustering decisions. In fact, clustering decisions are ideally load-aware, so as to minimize the number of active BBUs while providing acceptable quality of service.

Unlike the state-of-the-art approaches, we address in this paper the joint user association and RRH clustering problem. Our objective is to maximize the network throughput, while minimizing the network power consumption. As this problem is a mixed integer non-linear programming problem, it can be solved through exhaustive search. However, the computational complexity becomes intractable as the network size increases. Therefore, we decouple our joint problem into two sub-problems: the user association (UA) sub-problem and the RRH clustering (RC) sub-problem. These sub-problems are iteratively solved until convergence, or in other terms until no more user-RRH associations and RRH clustering are to be further modified.

II. Related Work

As the user association and the RRH clustering problems have an important influence on the network performance, more precisely throughput, and the network power consumption, they need to be carefully addressed. Several works have tackled the two problems independently. The works in [1], [2] and [3] focused on the clustering problem. In [1], authors proposed a dynamic clustering algorithm, where RRHs that induce the strongest received signal powers are grouped together. The objective is to maximize the network spectral efficiency. In [2], the RRH clustering is formulated as a modified bin packing problem. The aim is to minimize the number of active BBUs, and consequently the network power consumption, without compromising user quality of service. In [3], RRH clustering was portrayed as a coalition formation game, where the objective is to optimize the network throughput, power consumption, and handover frequency. The works in [4], [5] tackled the user association problem. A user association optimization problem was formulated in [4] to minimize the network latency. To solve the latter, a three-phase search algorithm was introduced. In [5], the authors tackled the same problem, where the objective is to minimize the power consumption under downlink and uplink QoS constraints. Furthermore, few works considered the joint problem of user association and RRH clustering. The authors in [6] present one of the works addressing the dependency between the two problems. They propose a dynamic two-stage design. First stage, Branch & Cut algorithm is used to find the proper user-RRH association. Second stage, BBU-RRH clustering is modeled as a Multiple Knapsack Problem, and is based on the output of the first stage. However, inter-cluster interferences are ignored, which have a serious impact on network performances as demonstrated in [7]. To reduce the energy consumption, the authors in [8] propose an energy-saving algorithm with joint user association and clustering strategies. First, to solve the user association sub-problem, an optimal association policy is applied, based on load balancing and energy efficiency. Second, the clustering sub-problem is modeled as an integer linear programming, based on the location and load of the base stations. Yet, this study overlooks user quality of service and does not iteratively solve the two sub-problems until reaching a stable and jointly efficient solution.

In this paper, the contributions of our work can be summarized as follows:

- We formulated the joint user association and RRH clustering problem, taking into account inter-cluster interferences. Our objective is to maximize the network throughput and to minimize the network power consumption.
- To deal with the high computational complexity of the joint problem, we decouple it into two sub-problems: the user association (UA) sub-problem and the RRH clustering (RC) sub-problem. Further, to find a jointly efficient solution, these sub-problems are sequentially and iteratively solved until convergence, or in other terms until no more user-RRH associations and RRH clustering need to be further modified.
- We propose a heuristic, based on the merge-and-split rules, to solve the RC sub-problem. This solution can adapt to various traffic types (*e.g.,* elastic and inelastic traffic) and provides very close performances to that of the optimal clustering, with significantly lower computational complexity.

The rest of this paper is organized as follows. Section III describes the system model. In Section IV, we provide a framework for the joint optimization of user association and RRH clustering. Our iterative approach to solve the joint problem is introduced in Section V. Simulation results are presented in Section VI. Finally, concluding remarks are provided in Section VII.

III. System Model

Consider R RRHs denoted by the set $\mathcal{R} = \{r_1, r_2, \cdots, r_R\}$ and B BBUs denoted by the set $\mathcal{B} = \{b_1, b_2, \cdots, b_B\}$. While the RRHs are distributed across multiple sites, the BBUs are pooled in a cloud data center, as illustrated in Fig. 1. We further denote by $\mathcal{U} = \{u_1, u_2, \cdots, u_U\}$ the set of active users. X_{ur}, Y_{rb}, H^r, and K^b are binary variables that define the user association and the RRH clustering respectively. X_{ur} is equal to 1 if user u is attached to RRH r, and zero otherwise, and Y_{rb} is equal to 1 if RRH r is attached to BBU b, and zero otherwise. Furthermore, H^r and K^b are two binary variables, which are equal to one if RRH r and BBU b are turned on respectively and zero otherwise. We assume that each user is served by at most one RRH, and each RRH can be associated with at most one BBU. Moreover, we denote by d_u the throughput demand of user u.

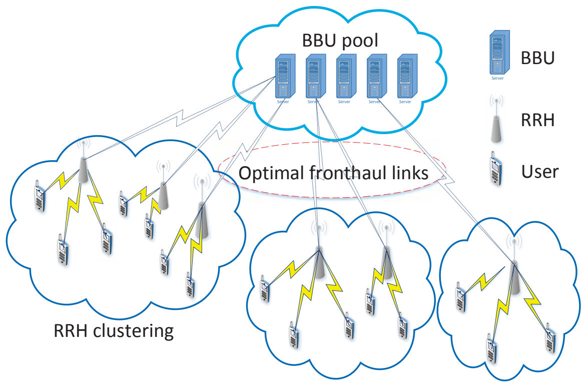

Fig. 1. The C-RAN architecture.

The SINR of user u when attached to RRH r, that is mapped to BBU b, is given as:

$$\Gamma_{urb} = \frac{P_r G_{ur}}{N_0 + \sum_{r' \neq r} (1 - y_{r'b}) P_{r'} G_{ur'}}, \tag{1}$$

where P_r is the transmit power of RRH r, G_{ur} is the channel gain between user u and RRH r, and N_0 is the thermal noise power. Note that $\sum_{r' \neq r} (1 - y_{r'b}) P_{r'} G_{ur'}$ represents the inter-cluster interferences caused by the RRHs that are not associated with BBU b, which means there does not exist intra-cluster interferences between RRHs associated to the same BBU.

The average spectral efficiency in BBU b, denoted by $\hat{\eta_b}$, can be written as follows:

$$\hat{\eta_b} = \frac{1}{u_b} \sum_{r \in \mathcal{R}} \sum_{u \in \mathcal{U}} X_{ur} Y_{rb} \log(1 + \Gamma_{urb}), \tag{2}$$

where u_b represents the number of users sharing the radio resources of BBU b and can be expressed as:

$$u_b = \sum_{r \in \mathcal{R}} \sum_{u \in \mathcal{U}} X_{ur} Y_{rb}. \tag{3}$$

Throughput demands of RRH r, denoted by d_r, is the sum of throughput demands of the users that are served by RRH r and can be written as follows:

$$d_r = \sum_{u \in \mathcal{U}} X_{ur} d_u. \tag{4}$$

A. Throughput Model

We denote by T_{rb} the average throughput perceived by RRH r, that is mapped to BBU b. We consider that radio resources in BBU b are shared amongst its associated RRHs proportionally to their throughput demands. However, the allocation of each RRH is limited to its throughput demand. Thus, the average throughput achieved in RRH r can be expressed as follows:

$$T_{rb} = [\frac{T_b^m}{\max{(T_b^m, \sum_{r\in\mathcal{R}} Y_{rb} d_r)}}] \cdot d_r, \tag{5}$$

where T_b^m is the maximum throughput achieved by BBU b and is defined as follows:

$$T_b^m = W_b \cdot \hat{\eta_b}, \tag{6}$$

where W_b is the channel bandwidth in BBU b.

We denote by T_b the average throughput achieved in BBU b. It is the sum of throughputs achieved by the RRHs that are attached to BBU b and can be expressed as follows:

$$T_b = \sum_{i\in\mathcal{R}} Y_{rb} T_{rb}. \tag{7}$$

Moreover, we denote by T_{total} the total throughput achieved in the network. It is defined as the sum of throughputs achieved by active BBUs as presented in Equation (7). Thus, T_{total} can be written as:

$$T_{total} = \sum_{b\in\mathcal{B}} T_b. \tag{8}$$

B. C-RAN Power Consumption Model

According to [9], the power consumed in the C-RAN architecture is modeled as the sum of two terms, the power consumed by all BBUs at the baseband processing pool, and the power consumed by all RRHs. Thus, the total network power consumption can be expressed as:

$$P_{total} = \sum_{b\in\mathcal{B}} P_b + \sum_{r\in\mathcal{R}} P_r, \tag{9}$$

where P_b and P_r respectively denote the power consumed by BBU b and that at RRH r.

As for the power consumption at BBU b, P_b is a linear function of the throughput achieved in BBU b. It can be expressed as:

$$P_b = \begin{cases} \lambda + \mu \cdot T_b, & \text{if } K^b = 1, \\ 0, & \text{otherwise,} \end{cases} \tag{10}$$

where λ represents the power consumption of BBU b in active mode, and μ is the variation coefficient of P_b as a function of T_b.

Similarly, the power consumption at RRH r, can be expressed as:

$$P_r = \begin{cases} P^0 + \delta P_r, & \text{if } H^r = 1, \\ P^s, & \text{otherwise,} \end{cases} \tag{11}$$

where δ is the power amplifier efficiency, P_r is the transmit power of RRH r, and P^0 and P^s are the additional power consumed by RRH r independently of P_r in active mode and sleep mode respectively.

IV. Joint User Association and RRH Clustering Problem

The user association and the RRH clustering are two mutually dependent problems. The user association influences RRH load conditions and consequently clustering decisions. In fact, clustering decisions need to be load-aware, so as to minimize the number of active BBUs while providing acceptable quality of service. Furthermore, reducing the number of active BBUs decreases the total interference level and the network power consumption. Nevertheless, crowded BBUs (*i.e.,* to which overloaded RRHs are associated) lead to resource shortage and have a crucial impact on user throughputs and consequently on user associations.

A. Network Utility Function

We define the network utility function U as a linear combination of the total network throughput T_{total} and the total network power P_{total}:

$$U = \alpha\alpha' T_{total} - \beta\beta' P_{total}, \tag{12}$$

where α' and β' are two normalizing constants, and α and β are the weighting factors that tune the tradeoff between the two components of U. Note that α and β are between 0 and 1, and $\alpha + \beta = 1$.

B. Optimization Problem Formulation

Our optimization problem ($\mathcal{P}$) consists in finding the optimal user association and RRH clustering decisions, that maximize the network utility U. Therefore, ($\mathcal{P}$) can be written as follows:

$$\underset{X,Y}{\text{maximize}} \quad U(X,Y) \tag{13}$$

$$\text{subject to} \quad \sum_{r\in\mathcal{R}} X_{ur} \leq 1, \ \forall u \in \mathcal{U} \tag{14}$$

$$\sum_{b\in\mathcal{B}} Y_{rb} \leq 1, \ \forall r \in \mathcal{R} \tag{15}$$

$$X_{ur} \leq H^r, \ \forall (u,r) \in \mathcal{U} \times \mathcal{R} \tag{16}$$

$$Y_{rb} \leq K^b, \ \forall (r,b) \in \mathcal{R} \times \mathcal{B} \tag{17}$$

$$X_{ur}, Y_{rb}, H^r, K^b \in \{0,1\}, \forall (u,r,b) \tag{18}$$

Constraints (14) ensure that a user must be connected to at most one RRH. Constraints (15) ensure that each RRH can at most be mapped to one BBU. Constraints (16) indicate that a given RRH is turned on only when it serves at least one user. Constraints (17) state that a given BBU is activated only if at least one RRH is associated to it. Finally, constraints (18) indicate that all the decision variables, namely X_{ur}, Y_{rb}, H^r, and K^b are binary.

C. Complexity Analysis

Our problem ($\mathcal{P}$) is a mixed integer nonlinear programming problem, that is NP-hard. The optimal solution can be obtained through exhaustive search. However, this requires exploring all possible user-RRH associations in all possible RRH-BBU configurations. In fact, the number of possible user-RRH associations is R^U. Besides, the number of possible RRH-BBU configurations is given by the R-th Bell number, denoted by B_R, and grows rapidly with R. Consequently, the computational complexity for obtaining the optimal solution is in $O(B_R.R^U)$. The exhaustive search is thus extremely computational intensive and becomes prohibitive even for medium-sized networks. To overcome the complexity of the joint problem, we propose in section V to decouple it into two sub-problems, namely the user association (UA) sub-problem and the RRH clustering (RC) sub-problem, and to sequentially and iteratively solve them until convergence is achieved. Such an iterative approach allows to reach jointly efficient solutions.

V. Heuristic solution for the Joint Problem

To overcome the complexity of the joint problem, we present in this section an iterative approach that allows reaching stable and jointly efficient solutions. The joint problem is decoupled into two sub-problems: the user association (UA) sub-problem and the RRH clustering (RC) sub-problem. These two sub-problems are sequentially and iteratively solved, as presented in Fig. 2, until convergence is reached. More precisely, assuming an initial RRH clustering, the UA sub-problem is first solved. Then, considering the outputs of the UA sub-problem, the RC sub-problem is solved. Further, depending on the clusters that have been recently formed, user associations may be reconsidered. This is repeated until convergence, or in other terms until no more user-RRH associations and RRH clustering need to be further modified. Thus, the mutual dependence between the UA sub-problem and the RC sub-problem is taken into account, leading to jointly efficient solutions.

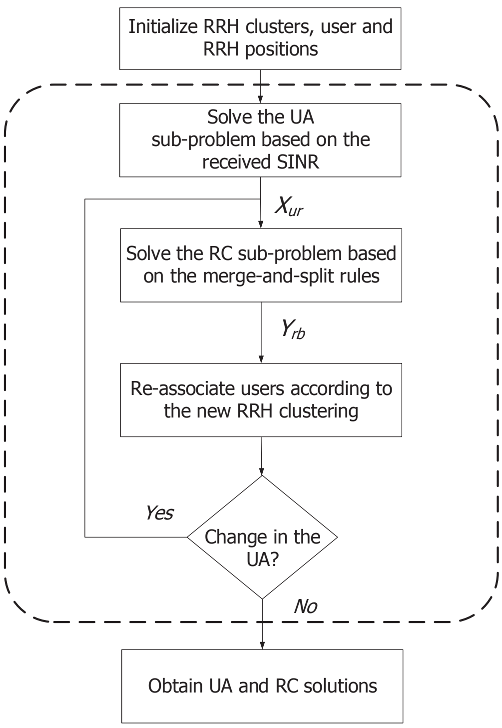

Fig. 2. Iterative approach for the joint user association and RRH clustering problem.

A. UA Sub-problem

The optimal user association sub-problem can be solved through exhaustive search. Although the computational complexity is reduced to be in $O(R^U)$, the optimal solution remains practically intractable particularly for large U. For that, we resort in this article to a low-complexity heuristic algorithm, based on the received SINR, to determine user-RRH associations. As a matter of fact, user u is associated with RRH r^* whose radio signals are the best received: $r^* = \text{argmax}_r \; \Gamma_{urb}$. This heuristic maximizes users radio conditions and enhances network spectral efficiency.

B. RC Sub-Problem

The optimal RRH clustering sub-problem can also be solved through exhaustive search. This requires exploring all possible partitions of $\mathcal{R}$ and selecting the one that maximizes the network utility. Although the computational complexity is reduced to be in $O(B_R)$, the optimal solution remains intractable for large R. Therefore, we propose in this article a low-complexity heuristic algorithm, based on the merge-and-split rules [10], to solve the RC sub-problem. More precisely, based on the merge-and-split rules, the RRHs collaborate and organize themselves into disjoint independent clusters, in a way to maximize the network utility:

- Clusters $\{c_1, c_2, \cdots, c_l\}$ are merged into one, if the resulting cluster provides a higher network utility:

$$U(\bigcup_{i=1}^{l} c_i) > \sum_{i=1}^{l} U(c_i) \tag{19}$$

  The merging process ends when no more preferred clusters can be further formed.
- A cluster $\bigcup_{i=1}^{l} c_i$ is splitted into smaller ones $\{c_1, \ldots, c_l\}$, if this leads to a higher network utility:

$$\sum_{i=1}^{l} U(c_i) > U(\bigcup_{i=1}^{l} c_i) \tag{20}$$

  The splitting process ends when no more clusters are to be preferably broken into.

The merging and splitting processes are repeated until convergence, or in other terms until no more merge-and-split can be further done. According to [10], our heuristic leads to a $\mathbb{D}_{hp}$-stable partition, since it consists of successive merge-and-split operations.

1) Complexity Analysis: The computational complexity is determined by the number of attempts for the merge-and-split operations. In the worst case scenario, the first RRH initiates $(R-1)$ merging attempts, the second initiates $(R-2)$ iterations, and so on. Consequently, the total number of merging attempts will be $(R(R-1)/2)$. Thus, the complexity of the merging process is in $O(R^2)$. However, in practice, the merging process requires a significantly less number of attempts: once a cluster is formed, it does not always require to go through all the merging attempts. Furthermore, in the worst case scenario, the complexity of the splitting process is in $O(B_R)$. This involves finding all the possible partitions of $\mathcal{R}$. Yet, in practice, the splitting process is restricted to the clusters that have already been formed and is not performed over all the RRHs in $\mathcal{R}$. As the network utility takes into account the network total throughput, cluster sizes are usually kept small. As a result, the complexity of the splitting process is practically reasonable.

VI. Simulation Results

In this section, we evaluate the performance of our heuristic iterative solution. We also compare our heuristic solution for the RC sub-problem with the optimal solution obtained through exhaustive search, the no-clustering solution, where one BBU is exclusively dedicated to each RRH, and the grand coalition, where all RRHs are associated with a single BBU.

We use Matlab for simulations, and we consider a 7-cell network: a central RRH is surrounded by a ring of 6 immediately adjacent RRHs. The Cost-231 Hata model is used to compute the channel gains. We consider 500 simulation snapshots. Each is repeated until convergence is reached. All performance metrics are averaged and shown with 95% confidence intervals. The simulation parameters are presented in Table I.

TABLE I
Simulation Parameters

Parameter	***Value***
α	0.5
β	0.5
$P_r, \forall r$	10 W
P^0	6.8 W
P^s	4.3 W
δ	4
λ	40 W
μ	0.6 W/(Mb/s)
$W_b, \forall b$	20 MHz
N_0	−174 dBm/Hz

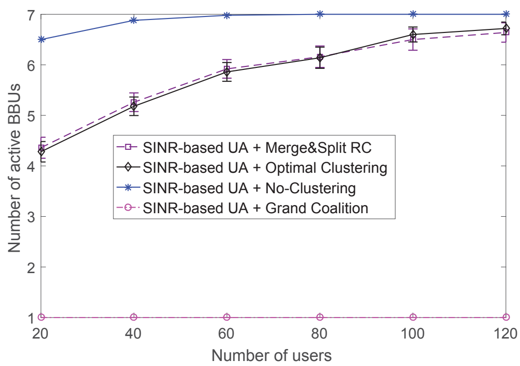

Fig. 3. Number of active BBUs as a function of the number of users

Fig. 3 illustrates the number of active BBUs as a function of the number of users. Regardless of the number of users in the network, the number of activated BBUs given by the grand coalition scheme is unchanged (*i.e.,* equal to 1), since all RRHs are mapped to one BBU. However, in the no-clustering scheme, this number increases with the number of active RRHs, or equivalently the number of users. As a matter of fact, a BBU is exclusively dedicated to each active RRH. Moreover, our heuristic and optimal solutions effectively reduce the number of active BBUs mainly at low load conditions (*i.e.,* number of users below 60). This significantly decreases both the inter-cluster interferences and the power consumption (cf. Fig. 4 and 6) in comparison with the no-clustering solution.

Furthermore, Fig. 4 shows the user interference as a function of the number of users in the network. Inter-RRH interferences can be avoided by activating one BBU as in the grand coalition method. However, limiting the number of active BBUs provides the lowest user throughputs as illustrated in Fig. 5. Besides, the no-clustering solution leads to the highest interference level, as it actives the highest number of BBUs (cf. Fig. 3). Moreover, our heuristic and optimal solutions reduce the inter-BBU interference through reducing the number of active BBUs. Note that, for a large number of users, the gap between the no-clustering, our heuristic and the optimal solutions decreases as all of them activate almost the same number of BBUs.

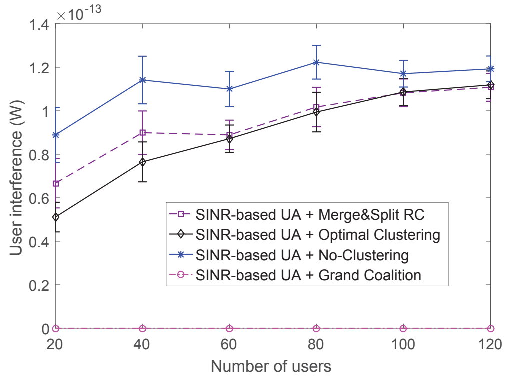

Fig. 4. User interference as a function of the number of users

Fig. 5 shows the user throughput as a function of the number of users. The throughput achieved by a user depends on the number of available resources as well as the endured interference. Since the grand coalition activates only one BBU (*i.e.,* provides very limited resources without interference as shown in Fig. 4), it achieves the lowest user throughput. However, the no-clustering method ensures the highest user throughputs owing to the availability of radio resources, but at the cost of high inflicted interference (*i.e.,* it maximizes the number of active BBUs). Moreover, our heuristic and optimal solutions achieve very close user throughputs to that of the no-clustering scheme while providing less interference and power consumption as illustrated in Fig. 4 and 6.

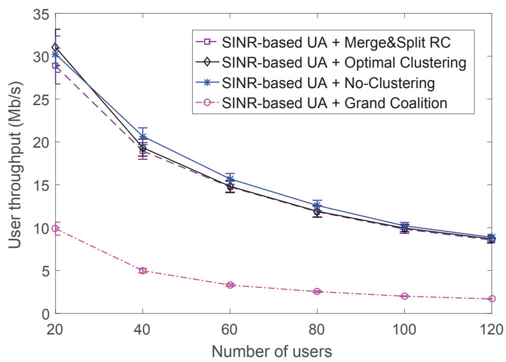

Fig. 5. User throughput as a function of the number of users

Moreover, the power consumption depends on the number of active BBUs and RRHs and their realized throughputs (according to Eq. (10)). As shown in Fig. 6, the grand coalition solution minimizes the power consumption by activating only one BBU. As for the no-clustering solution, it leads to the highest power consumption in comparison with our heuristic, the optimal and the grand coalition solutions. Moreover, by reducing the number of active BBUs, our heuristic and the optimal solution consume less power than the no-clustering method. Yet, they provide close user throughputs to the no-clustering solution (cf. Fig. 5).

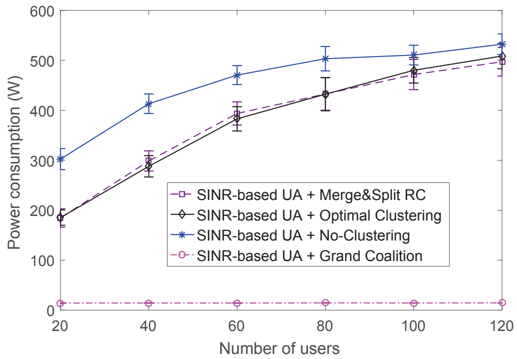

Fig. 6. Power consumption as a function of the number of users

As illustrated in Fig. 7, the network utility achieved by our heuristic and the optimal solutions outperform the two state-of-the-art methods regardless of the number of users in the network. In fact, they realize a good trade-off between user throughput and overall power consumption to maximize the network utility under all load conditions.

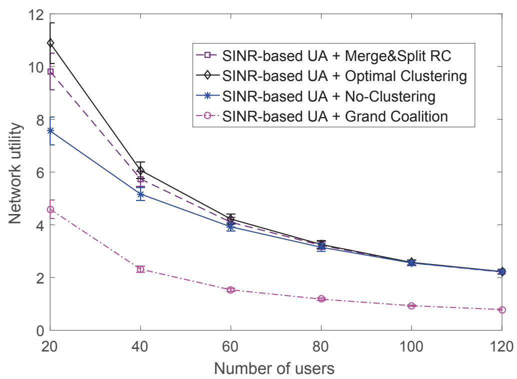

Fig. 7. Network utility as a function of the number of users

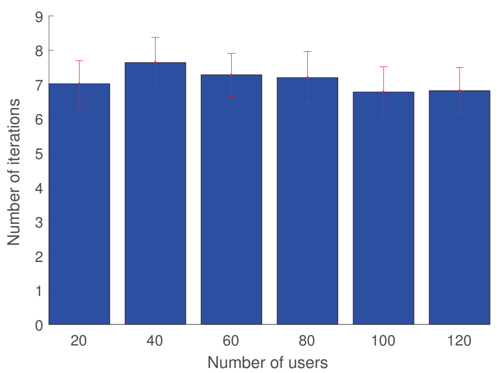

Fig. 8. Number of iterations as a function of the number of users

We show in Fig. 8 the number of iterations, or equivalently the number of successive merge-and-split operations, our heuristic requires to reach a $\mathbb{D}_{hp} - stable$ partition. While the optimal exhaustive search solution needs 877 iterations to find the optimal partition, our proposed heuristic converges rapidly within few iterations (a maximum of 8 iterations). Yet, as discussed earlier, our heuristic provides very close performances to that of the optimal one particularly in terms of throughput, power consumption and utility function.

A. *Performance evaluation in large networks*

In this section, we highlight the importance of cluster formation on interference mitigation and its impact on network performance. In large networks, the interference becomes significantly large. Thus, the role of RRH clustering becomes more pronounced as an interference mitigation technique. In order to examine the impact of interference, we consider a network composed from 19 RRHs as presented in Fig. 9. Since finding the optimal clusters by exhaustive search is impractical in such network, we use our proposed heuristic solution to solve the RC sub-problem.

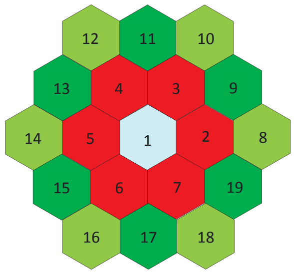

Fig. 9. Network with 19 RRHs

We start by the variation of the number of active BBUs as a function of the number of users in the network. Fig. 10 shows that our heuristic solution avoids turning on all BBUs for high load conditions (*i.e.,* 120 users) contrarily to the case shown in Fig. 3 where almost all BBUs are activated by the same algorithm (*i.e.,* 13 activated BBUs from 14). In fact, activating more BBUs leads to increased interference (among RRHs belonging to different BBUs), which has a seriously negative impact on large scale network performance. Thus, by reducing the number of active BBUs, the heuristic solution allows a reduction of the interference level in comparison with no-clustering scheme (cf. Fig. 11). Moreover, with less radio resources, our algorithm provides very close user throughput to that of the no-clustering method as well as less power consumption, as illustrated in Fig. 12 and Fig. 13. Consequently, by reducing both the user interference and the power consumption while preserving the user throughput, our heuristic solution introduces a significant performance gain for a large network size. Therefore, the heuristic outperforms the no-clustering method with a relatively large gap (cf. Fig. 14) comparing to the case seen in Fig. 7 where the gap between the two methods is too tight especially at high load condition.

VII. Conclusion

In this paper, we consider the joint user association and RRH clustering problem in cloud radio access networks. This problem is formulated as a mixed integer optimization problem with the objective of maximizing the overall network throughput and reducing the network power consumption. Since such problem is NP-hard, we propose to decompose it into two sub-problems: the user association (UA) and the RRH clustering (RC) sub-problems. These two sub-problems are sequentially and iteratively solved until convergence is reached. Such an iterative approach allows reaching stable and jointly efficient solutions. Moreover, we present a low-complexity heuristic, based on the merge-and-split rules, to solve the RC sub-problem. Simulation results show that our proposed heuristic achieves the highest network utility in comparison with the two state-of-the-art methods: the grand coalition and the no-clustering. In addition, it achieves very close performances to the optimal exhaustive search method. Further, our heuristic solution provides a significant performance gain in large networks in comparison with the two state-of-the-art methods.

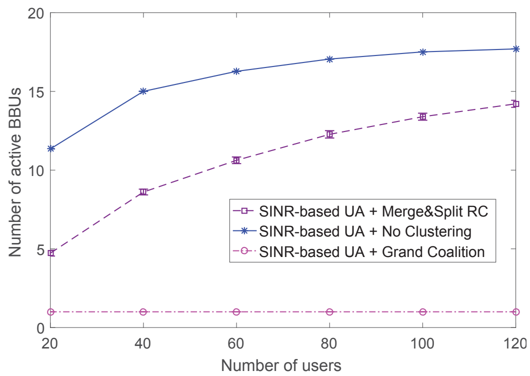

Fig. 10. Number of active BBUs as a function of the number of users

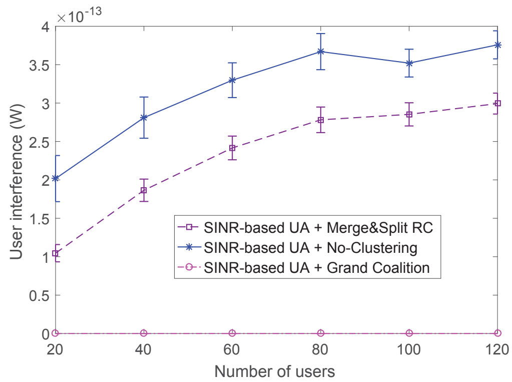

Fig. 11. User interference as a function of the number of users

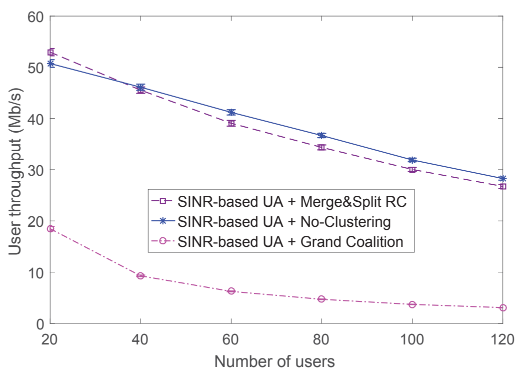

Fig. 12. User throughput as a function of the number of users

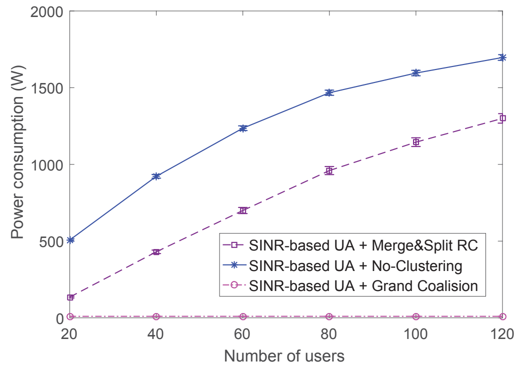

Fig. 13. Power consumption as a function of the number of users

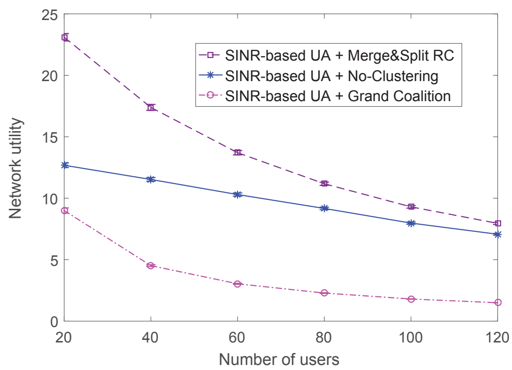

Fig. 14. Network utility as a function of the number of users

REFERENCES

[1] I. D. Garcia, N. Kusashima, K. Sakaguchi, and K. Araki, "Dynamic cooperation set clustering on base station cooperation cellular networks," in *21st Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, Sept 2010, pp. 2127–2132.

[2] K. Boulos, M. E. Helou, and S. Lahoud, "RRH Clustering in Cloud Radio Access Networks," in *Applied Research in Computer Science and Engineering (ICAR), 2015 International Conference on*, Oct 2015.

[3] H. Taleb, M. E. Helou, K. Khawam, S. Lahoud, and S. Martin, "Centralized and distributed rrh clustering in cloud radio access networks," in *2017 IEEE Symposium on Computers and Communications (ISCC)*, July 2017, pp. 1091–1097.

[4] H. Zhang, W. Wang, X. Li, and H. Ji, "User association scheme in cloud-ran based small cell network with wireless virtualization," in *2015 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, April 2015, pp. 384–389.

[5] S. Luo, R. Zhang, and T. J. Lim, "Downlink and uplink energy minimization through user association and beamforming in c-ran," *IEEE Transactions on Wireless Communications*, vol. 14, no. 1, pp. 494–508, Jan 2015.

[6] M. Y. Lyazidi, N. Aitsaadi, and R. Langar, "Dynamic resource allocation for cloud-ran in lte with real-time bbu/rrh assignment," in *2016 IEEE International Conference on Communications (ICC)*, May 2016.

[7] K. Boulos, M. E. Helou, M. Ibrahim, K. Khawam, H. Sawaya, and S. Martin, "Interference-aware clustering in cloud radio access networks," in *2017 IEEE 6th International Conference on Cloud Networking (CloudNet)*, Sept 2017.

[8] X. Li, F. Jin, R. Zhang, and L. Hanzo, "Joint cluster formation and user association under delay guarantees in visible-light networks," in *2016 IEEE Global Communications Conference (GLOBECOM)*, Dec 2016.

[9] G. Auer, V. Giannini, C. Desset, I. Godor, P. Skillermark, M. Olsson, M. A. Imran, D. Sabella, M. J. Gonzalez, O. Blume, and A. Fehske, "How much energy is needed to run a wireless network?" *IEEE Wireless Communications*, vol. 18, no. 5, pp. 40–49, October 2011.

[10] K. R. Apt and T. Radzik, "Stable Partitions in Coalitional Games," arXiv:cs/060532v1, 2006.