Centralized and Distributed RRH Clustering in Cloud Radio Access Networks

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***Abstract*—Cloud Radio Access Network (C-RAN) is a promising technology to improve user quality of service and reduce network capital and operating costs. The key concept behind C-RAN is to break down the conventional base station into a Base Band Unit (BBU) and a Remote Radio Head (RRH), and to pool BBUs from multiple sites into a single geographical point. Moreover, to achieve statistical multiplexing gain, RRHs should be efficiently clustered: many RRHs may be mapped into a single BBU. In this article, RRH clustering is formulated as a coalition formation game where RRHs collaborate and organize themselves into disjoint independent clusters, in a way to optimize network throughput, power consumption, and handover frequency. An optimal centralized solution, based on exhaustive search, is presented. We also propose a distributed algorithm, based on the merge-and-split rule, to form RRH clusters. Simulation results show that our centralized solution adapts to network load conditions and outperforms the no-clustering method, where only one RRH is assigned to each BBU, and the grand coalition method, where all RRHs are assigned to a single BBU. More importantly, our distributed algorithm achieves very close performance to the optimal solution, with significantly lower computational complexity.**

I. Introduction

To cope with the huge demand for capacity, base stations are to be densely deployed in next-generation networks [1]. Therefore, and while operator revenues stay flat or even decline, network capital and operating costs significantly increase [2]. In this context, Cloud Radio Access Network (C-RAN) was introduced as a promising technology to improve network performance, while reducing costs. The key concept behind C-RAN is to break down the conventional base station into a digital function unit, known as the BaseBand Unit (BBU), and a low-cost radio function unit, known as the Remote Radio Head (RRH). While RRHs are distributed across multiple sites, BBUs are pooled in a cloud data center. Moreover, RRHs are connected to BBUs through high-performance optical fronthaul links. Therefore, traditionally centralized or co-located functionalities need to be split over the C-RAN. RRHs only keep basic transmission and reception functionalities, whereas BBUs handle computationally intensive baseband processing.

Conventionally, each BBU is assigned to one RRH. In this setting, radio and computing resources, dimensioned for the peak-load conditions, are exclusively dedicated to one RRH. This leads to inefficient resource utilization, particularly at low-load conditions. However, it is possible to achieve statistical multiplexing gain by clustering RRHs adequately. Accordingly, many RRHs may be mapped to a single BBU, sharing radio and computing resources. Such clustering reduces network capital and operating expenditures, possibly at the cost of network performance.

A real challenge is to form RRH clusters, adaptively to network load conditions, in a way to reduce network costs (*i.e.,* reduce computing resources and power consumption), without degrading user quality of service. In this article, RRH clustering is formulated as a coalition formation game: RRHs collaborate and organize themselves into disjoint independent clusters, in a way to maximize network utility. This function reflects network performance, more precisely throughput and handover frequency, as well as network power consumption. An optimal centralized approach based on exhaustive search and a distributed approach based on the merge-and-split rule are further introduced to derive Utilitarian and Pareto solutions. While Utilitarian solutions maximize global network utility (*i.e.,* total social welfare), Pareto solutions consider rather RRH individual utilities.

II. Related Work

Cloud radio access networks have triggered considerable interest among researchers in the past few years. Several papers have addressed the RRH clustering problem, so as to enhance radio and energy resource management. The authors in [3] proposed two BBU-RRH mapping schemes for C-RAN: the first scheme is a semi-static one that determines the mapping between RRHs and BBUs to accommodate peak hour traffic loads. The second scheme is an adaptive one where connections between BBUs and RRHs are re-examined at time intervals depending on BBU resource usage. The main objective of both schemes is to decrease the number of active BBUs leading to a reduction in network power consumption as well as to an effective utilization of baseband resources. Yet, this study does not take into account user quality of service. In [4], the RRH clustering problem was formulated as a bin packing problem, where the objective is to minimize network power consumption without compromising user quality of service. We note that the proposed solution can not adapt to different operator strategies, since no compromise can be done on user-level quality of service. Besides, the impact of RRH clustering on handovers was not explicitly considered. In [5], a coalition formation game is used to model RRH clustering: RRHs collaborate and form clusters in a way to maximize their throughput. However, this study does not deal with network power consumption nor handover frequency. Further work in [6] and [7] focused on improving network throughput, by reducing inter-cluster interferences, without taking into account neither network power consumption nor handover frequency.

The contributions of our work are listed below:

- We formulate the RRH clustering problem as a coalition formation game, that encompasses previous work. Our approach introduces a tunable balance among network throughput, handover frequency, and power consumption.
- Existing implementations of clustering are based on the presence of a central unit. This unit is responsible for the formation of clusters as in [3] and [4]. Our work considers both approaches: the centralized approach and the distributed approach. The first provides optimal solutions, but at the cost of high computational complexity. The latter achieves close-to-optimal performances with low complexity and is efficient for implementation in practice.
- The weights associated to throughput, power consumption, and handover frequency in the clustering decision-making allow us to investigate the tradeoffs between such performance indicators, making our solution flexible. The importance of such weight associations is that operators will have the ability to apply different strategies. For example, an operator can prefer to slightly sacrifice user quality of service to consume less power or to meet user quality of service at the cost of increased network power consumption.
- To the best of our knowledge, this paper is the first to consider an explicit handover model depending on user speed, cluster shape and size to consider user mobility in the clustering decision-making.

The rest of this paper is organized as follows. System model is described in section III. Section IV presents our utility function. Centralized and distributed approaches for RRH clustering are introduced in section V. Simulation results are discussed in section VI. Section VII concludes the paper.

III. C-RAN Cluster Formation

A. System Model

Consider N distributed RRHs connected to a pool of BBUs through high-performance optical fronthaul links as shown in Fig. 1. Let R_n, $n = \{1, \ldots, N\}$, designate the N serving RRHs within the network. RRHs collaborate together to form disjoint independent clusters. d_n is the number of users that are assumed to be associated with RRH R_n. To meet their throughput requirements, R_n is considered to be in need of d_n radio resource units. Moreover, RRHs that are mapped to a single BBU (*i.e.,* forming one cluster) share the same radio resource pool, denoted by C_{BBU}.

B. Coalition Formation Game

RRH clustering is formulated as a coalition formation game deemed $(\mathcal{R}, \upsilon)$, where:

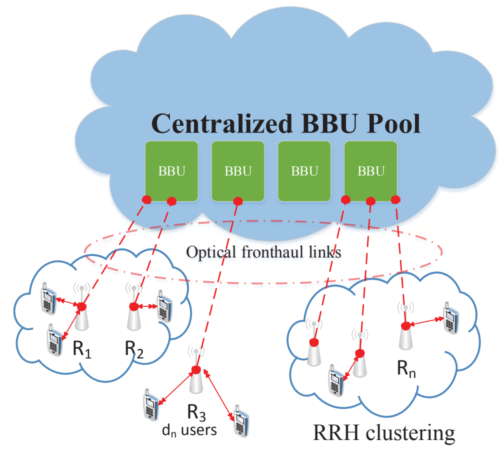


Fig. 1. The components of C-RAN clustering

- $\mathcal{R} = \{R_1, \ldots, R_N\}$ represents the set of players (RRH) that seek to form clusters. In addition, any coalition $S_i \subseteq \mathcal{R}$ represents an agreement between the RRHs in S_i to be associated with a single BBU. Besides, $\mathcal{S}$ is a coalitional structure defined as a partition of $\mathcal{R}$: $\mathcal{S} = \{S_1, \ldots, S_L\}$, such that $\forall\ i \neq j$, $S_i \cap S_j = \emptyset$ and $\bigcup_{i=1}^{L} S_i = \mathcal{R}$.
- υ represents the coalition value: $\upsilon(S_i)$ denotes the worth of coalition S_i, a real number that quantifies the cluster utility. In our work, υ reflects network performance, more precisely throughput and handover frequency, as well as network power consumption. Furthermore, $\upsilon(S_i)$ can be divided among the cluster members. The amount of utility that R_n receives from this division constitutes the RRH individual utility and is denoted by x_n.

C. Utilitarian Order vs Pareto Order

In our work, to compare coalitional structures, the following two orders are adopted:

1) Utilitarian order: this order focuses on global network utility (*i.e.,* total social welfare). Given two coalitional structures $\mathcal{S} = \{S_1, \ldots, S_L\}$ and $\mathcal{T} = \{T_1, \ldots, T_K\}$, RRHs prefer to gather up into $\mathcal{T}$ instead of $\mathcal{S}$, if the global network utility achieved in $\mathcal{T}$ is strictly greater than in $\mathcal{S}$:
$$\sum_{i=1}^{K} \upsilon(T_i) > \sum_{i=1}^{L} \upsilon(S_i). \quad (1)$$
2) Pareto order: this order considers RRH individual utilities instead of global network utility. Pareto clusters are actually formed so that it is not possible to increase any RRH utility without decreasing at least another RRH utility. More precisely, let x_n and y_n be the individual utilities of R_n, $n = \{1, \ldots, N\}$, as allocated by $\mathcal{T}$ and $\mathcal{S}$ respectively. $\mathcal{T}$ is preferred to $\mathcal{S}$ if at least one RRH in $\mathcal{T}$ manages to improve its utility (*i.e.,* $x_n \geq y_n$) without reducing the other RRH utilities.

IV. Utility Function

To form clusters according to the Utilitarian or Pareto orders, the coalition value (*i.e.,* cluster utility) and the RRH individual utility, or equivalently the RRH allocation from the cluster utility, need to be defined. In this paper, utility functions reflect network performance, more precisely throughput and handover frequency, as well as network power consumption at the cloud side.

In what follows, for illustration, we consider a cluster (*i.e.,* coalition) S_i formed by n_i RRHs (R_n, $n = \{1, \ldots, n_i\}$).

A. Throughput

The throughput achieved in cluster S_i, denoted by $TH^S(S_i)$, is proportional to the number of radio resource units allocated to R_n, $n = \{1, \ldots, n_i\}$. As a matter of fact, it is expressed as follows:

$$TH^S(S_i) = \eta_i \cdot \min(C_{BBU}, \sum_{n=1}^{n_i}(d_n)), \quad (2)$$

where η_i is the spectral efficiency of cluster S_i. Note that η_i depends on user radio conditions within cluster S_i and is mainly affected by inter-cluster interferences.

Radio resources in S_i are shared amongst its associated RRHs, namely R_n, $n = \{1, \ldots, n_i\}$, proportionally to their individual demands d_n. However, the allocation of each RRH is limited to its demand. The throughput achieved in R_n can then be expressed as follows:

$$TH^R(R_n) = [\frac{C_{BBU}}{\max(C_{BBU}, \sum_{n=1}^{n_i}(d_n))}] \cdot \eta\ d_n. \quad (3)$$

B. Power Consumption

The power consumed by cluster S_i at the cloud side (*i.e.,* by its serving BBU), denoted by $PC^S(S_i)$, is a linear function of the throughput achieved in S_i [8]:

$$PC^S(S_i) = \lambda + \mu \cdot TH^S(S_i), \quad (4)$$

where λ represents the minimum power consumed by an active BBU at zero loads (*i.e.,* supporting no traffic), and μ is the variation coefficient of PC^S as a function of TH^S.

Moreover, the power consumed by S_i is fairly divided among its RRHs. The allocation of R_n, denoted by $PC^R(R_n)$, can be written as follows:

$$PC^R(R_n) = \lambda_n + \mu \cdot TH^R(R_n), \quad (5)$$

where $\lambda_n = \frac{\lambda}{n_i}$, and $TH^S(S_i) = \sum_{n=1}^{n_i}(TH^R(R_n))$.

C. Handover

Signaling resulting from handovers introduces overhead and negatively impact network performances. Thus, cluster formation, taking into consideration inter-cluster handovers, is a solution to reduce signaling cost.

The handover frequency in cluster S_i, denoted by $HO^S(S_i)$, represents the number of mobiles moving away from the area covered by R_n, $n = \{1, \ldots, n_i\}$, and entering the area covered by another cluster, per time unit (*i.e.,* passing from one coalition to another). This term depends on user mobility model, as well as on coalition shape and size.

According to [9] and [10], and assuming that a mobile randomly moves in all directions, the average handover frequency per user can be expressed as follows:

$$\frac{\vartheta L^{S_i}}{\pi A^{S_i}}, \quad (6)$$

where ϑ is the average user speed, L^{S_i} is the perimeter of the border cluster S_i shares with other clusters, and A^{S_i} is the S_i area defined as the sum of the areas of R_n, $n = \{1, \ldots, n_i\}$.

Consequently, $HO^S(S_i)$ can be written as follows:

$$HO^S(S_i) = \frac{\vartheta . L^{S_i}}{\pi . A} . \sum_{n=1}^{n_i}(d_n). \quad (7)$$

Recall that $\sum_{n=1}^{n_i}(d_n)$ represent the number of mobiles within cluster S_i. Furthermore, $HO^S(S_i)$ is divided among R_n, $n = \{1, \ldots, n_i\}$, proportionally to L^{R_n} (the perimeter of the border R_n shares with other clusters). The allocation of R_n, denoted by $HO^R(R_n)$, can then be written as:

$$HO^R(R_n) = \frac{L^{R_n}}{L^{S_i}} . HO(S_i). \quad (8)$$

D. Utility Expression

The utility function of cluster S_i (*i.e.,* its coalition value) is a linear combination of $TH^S(S_i)$, $PC^S(S_i)$ and $HO^S(S_i)$. It is defined as follows:

$$U^S(S_i) = \alpha\alpha' TH^S(S_i) - \beta\beta' PC^S(S_i) - \gamma\gamma' HO^S(S_i), \quad (9)$$

where α, β and γ are respectively the weights of the throughput, power consumption, and handover, and α', β' and γ' are normalizing constants.

Similarly, the individual utility function of R_n can be written as:

$$U^R(R_n) = \alpha\alpha' TH^R(R_n) - \beta\beta' PC^R(R_n) - \gamma\gamma' HO^R(R_n). \quad (10)$$

We note that the sum of R_n utilities, $n = \{1, \ldots, n_i\}$ is equal to the utility of S_i.

V. Centralized and Distributed Approaches for RRH Clustering

Finding optimal coalitional structures involves either maximizing global network utility or focusing on improving RRH individual utilities. We present in this section a centralized approach, based on exhaustive search, and a distributed approach, based on the merge-and-split rule, to form RRH clusters according to either the Pareto order or the Utilitarian order.

A. Centralized Approach

A central unit computes the optimal RRH clustering using an exhaustive search algorithm. Starting from a random initial coalitional structure, such algorithm explores all possible partitions and selects the best one according to the adopted comparison order, namely either the Pareto order or the Utilitarian order. Note that the number of possible partitions, also known as the Bell number, grows rapidly with N. Starting with $N = 1$, the first Bell numbers are: 1, 2, 5, 15, 52, 203, 877, 4140, 21147, 115975, 678570... Thus, the exhaustive search becomes intractable for large N. A distributed approach is vital to overcome the complexity of the centralized approach.

B. Distributed Approach

We propose in this section a distributed heuristic based on the merge-and-split rule. The merge-and-split algorithm consists of two actions: breaking and forming a coalition [11]. Coalitions are merged into one, if the resulting coalition is preferred according to the selected comparison order (*i.e.,* Utilitarian or Pareto orders): $\{S_1, \ldots, S_l\}$ are merged together when:

$$\upsilon(\bigcup_{i=1}^{l} S_i) > \sum_{i=1}^{l} \upsilon(S_i) \tag{11}$$

Similarly, coalitions are splitted if this leads to a preferred clustering according to the selected order: $\bigcup_{i=1}^{l} S_i$ is splitted into $\{S_1, \ldots, S_l\}$ when:

$$\sum_{i=1}^{l} \upsilon(S_i) > \upsilon(\bigcup_{i=1}^{l} S_i) \tag{12}$$

1) Merge and Split Algorithm: we present in Algorithm 1 our distributed coalition formation heuristic, based on the merge-and-split rule.

The initial state corresponds to the no-clustering scenario, where only one RRH is mapped to a given BBU. Then, RRHs start to collaborate and organize themselves into preferable coalitional structure according to the selected comparison order (*i.e.,* Utilitarian or Pareto orders). The first RRH initiates $(N-1)$ merging attempts, the second initiates $(N-2)$ attempts, and so on. As a result, the total number of merging attempts will be $(N(N-1))/2$. The merging process ends with coalitional structure $\mathcal{W}$, when no more attempts are to be made or no preferred coalitions can be formed. Then, coalitions in $\mathcal{W}$ decide to split based on the selected order. Each coalition, formed of a relatively small number of RRHs, will go through the splitting process on its own. The splitting process ends with coalitional structure $\mathcal{S}$, when no more coalitions are to be preferably broken into. This is repeated until no more merge-and-split can be further done.

Algorithm 1: Distributed Coalition Formation

Initialize $\mathcal{S} = \mathcal{R}$ (non-cooperative RRHs)
repeat

Coalitions initiate the local search merge operation based on the selected order

$$\mathcal{W} = \text{Merge } (\mathcal{S}).$$

Coalitions in $\mathcal{W}$ decide to split based on the selected order

$$\mathcal{S} = \text{Split } (\mathcal{W}).$$

until *merge-and-split iteration terminates*;

Theorem (Partition Stability)**.** *Our distributed coalition formation algorithm leads to coalitional structure* $\mathcal{P} = \{P_1, \ldots, P_M\}$. *This partition is* $\mathbb{D}_{hp}$*-stable, since the following two conditions are satisfied* [12]:

- $\forall\ i \in \{1, \ldots, M\}$, and for each partition $\{C_1, \ldots, C_B\}$ of the coalition P_i
$$\upsilon(P_i) \geq \textstyle\sum_{j=1}^{B} \upsilon(C_j).$$
- $\forall\ T \subseteq \{1, \ldots, M\}$
$$\textstyle\sum_{i \in T} \upsilon(P_i) \geq \upsilon(\bigcup_{i \in T} P_i).$$

Proof: no more coalitions in $\mathcal{P}$, that result from sequential merge-and-split operations, are to be preferably formed or broken. If for any $i \in \{1, \ldots, M\}$, and for any partition $\{C_1, \ldots, C_B\}$ of P_i, we assume that $\sum_{j=1}^{B} \upsilon(C_j) > \upsilon(P_i)$, then the partition $\mathcal{P}$ can still be subject to a split operation. This contradicts the fact that $\mathcal{P}$ results from a termination of the merge-and-split iteration. Therefore, the first $\mathbb{D}_{hp}$-stability condition is verified. Similarly, we can prove that the second $\mathbb{D}_{hp}$-stability condition is verified. Otherwise, $\mathcal{P}$ can still be subject to a merge operation. ■

VI. Simulation Results

The numerical results were obtained using Matlab. We consider a network of 7 hexagonal cells. The simulations are based on 3 traffic load conditions. RRH demands are uniformly between 1 – 9 radio resource units at low load conditions, 10 – 49 at medium load conditions, and 50 – 100 at high load conditions. Simulation parameters are listed in Table I. For each traffic load scenario, simulations are repeated 1000 times. Performance metrics are averaged and shown with 95% confidence interval. In our simulation, we assume that the value of η_i is constant since the effect of the interference has been neglected.

TABLE I
Simulation Parameters

Parameter	*Value*
α	1
α'	1
β	0.5
β'	0.9
γ	0.5
γ'	333
υ	3 m/s
R	3 km
C_{BBU}	100 radio resource units
η_i	1 Mb/s per radio resource unit

A. Centralized Approach

We compare in this subsection our optimal centralized approaches using the Pareto order and the Utilitarian order, respectively denoted by Centralized Pareto and Centralized Utilitarian, with the grand coalition and the no-clustering methods. When the no-clustering solution assigns only one RRH to each BBU, the grand coalition one maps all RRHs to a single BBU.

1) Number of active BBUs: Fig. 2 illustrates the number of active BBUs for different traffic load conditions.

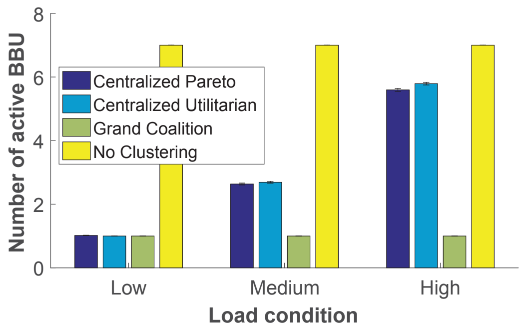


Fig. 2. Number of active BBUs in various load conditions

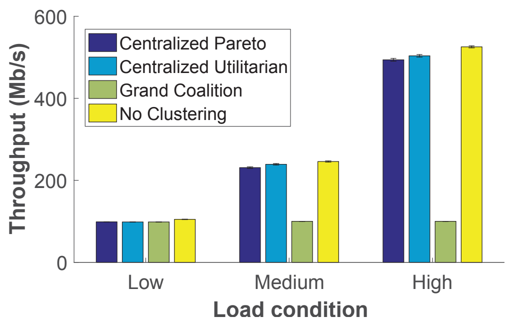


Fig. 3. Network throughput in various load conditions

At low load conditions, one active BBU is sufficient to handle user demands. Therefore, optimal solutions according to the Pareto order and the Utilitarian order are equivalent to that of the grand coalition method. At higher load conditions, the number of active BBUs given by Pareto and Utilitarian solutions grows to meet user demands. However, for the grand coalition and no-clustering solutions, this number stays constant oblivious of traffic conditions. As a result, Pareto and Utilitarian optimal solutions adapt the RRH clustering to traffic load conditions.

2) Throughput: as shown in Fig. 3, and since only one BBU is active, the grand coalition method provides a maximum throughput of 100 Mb/s. At medium load conditions, our optimal Pareto and Utilitarian solutions can double the throughput in comparison with the grand coalition solution. Moreover, they adapt cluster formation to network load conditions and achieve very close throughput to that of the no-clustering solution. We note that the no-clustering method maximizes the throughput, since all BBUs are always active.

In Fig. 4, we illustrate the utilization efficiency of radio resources for different traffic load conditions. It is defined as the ratio of the total number of radio resources used in all RRHs to the total number of radio resources available in active BBUs. Since the grand coalition solution provides very limited resources (100 resource units), their utilization is optimized. Yet, network throughput is very limited as noted in Fig. 3. Besides, although the no-clustering solution maximizes network throughput, available resources are underutilized particularly at low and medium load conditions. Moreover, centralized Pareto and Utilitarian solutions avoid resource wastage while providing close throughput to the no-clustering method.

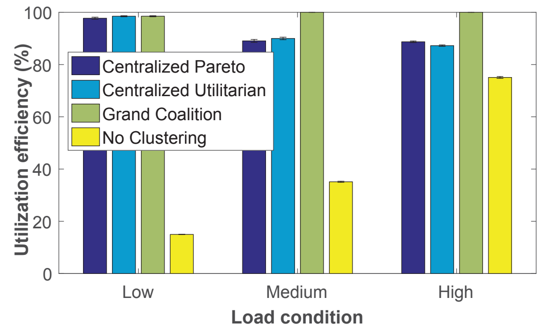


Fig. 4. Utilization efficiency in various load conditions

3) Power consumption: power consumption depends on the number of active BBUs and their realized throughput. As shown in Fig. 5, the grand coalition solution realizes the lowest power consumption, but at the cost of the lowest realized throughput (cf. Fig. 3). In addition, centralized Pareto and Utilitarian solutions consume lower power than the no-clustering solution mainly at low and medium load conditions. Yet, they provide close throughput to that of the no-clustering method.

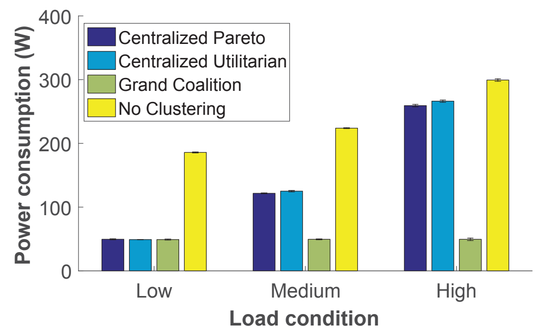


Fig. 5. Power consumption in various load conditions

Fig. 6 illustrates the power efficiency for different traffic load conditions. Power efficiency is defined as the ratio of the network throughput (*i.e.,* sum of cluster throughputs) to the network consumed power (*i.e.,* sum of cluster consumed power). Using the no-clustering method, $N = 7$ BBUs are active leading to the highest throughput and power consumption. However, as we note in Fig. 6 and mainly because of parameter λ in Eq. 4, the no-clustering solution achieves the lowest power efficiency typically at low load conditions. Besides, the grand coalition method consumes the lowest power. It has the highest power efficiency, but also the lowest throughput. Moreover, our approaches strike a very good tradeoff between throughput and power consumption, providing high power efficiency.

4) Handover: handover frequency depends on the cluster shape, size, and number of users. As shown in Fig. 7, the handover frequency is the lowest when using the grand coalition method. As a matter of fact, all RRHs belong to

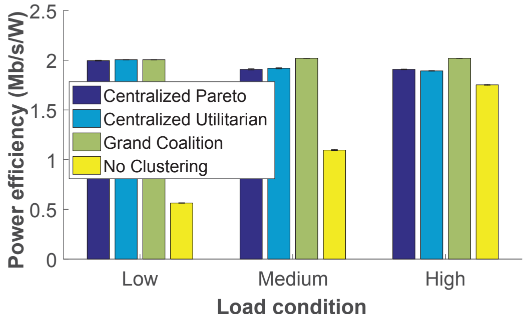


Fig. 6. Power efficiency in various load conditions

the same cluster, and no handover occurs when passing from one RRH to another. In addition, the no-clustering method leads to the highest handover frequency, as handovers are triggered whenever a user move from one RRH to another. Moreover, our approaches try to minimize the handover frequency without significantly degrading network throughput. Hence, more handovers are necessary when additional clusters are formed to cope with user throughput demands.

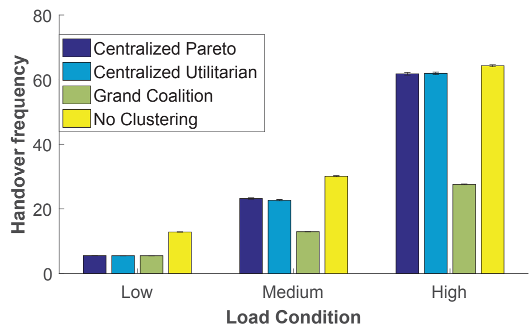


Fig. 7. Handover frequency in various load conditions

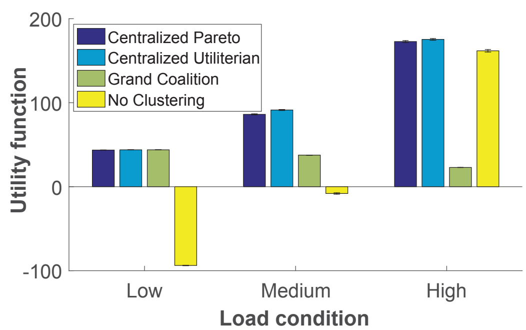


Fig. 8. Utility function in various load conditions

5) Utility function: as illustrated in Fig. 8, our approaches using the Pareto order and the Utilitarian order optimize the network utility, defined as a combination of network throughput, power consumption, and handover frequency. Note that by adjusting the weights of these parameters, namely α, β and γ, resulting clusterings may change in a way to maximize network utility, aligning with operator strategies. Consequently, our approaches provide a tunable tradeoff between throughput, power consumption, and handover frequency.

B. Distributed Approach vs. Centralized Approach

We compare in this subsection our centralized and distributed approaches using the Pareto order and the Utilitarian order. Simulations were performed at medium traffic load conditions.

1) Number of active BBUs: Figs. 9, 10(a), and 10(b) respectively show the number of active BBUs, the utility function, and the throughput for both our centralized and distributed approaches, using the Pareto order and the Utilitarian order. The optimal centralized approach, using the Utilitarian order, provides an upper bound on the network utility. It also brings the highest throughput. Moreover, our distributed approaches achieve very close performance to the centralized ones, in terms of number of active BBUs, utility function, and throughput.

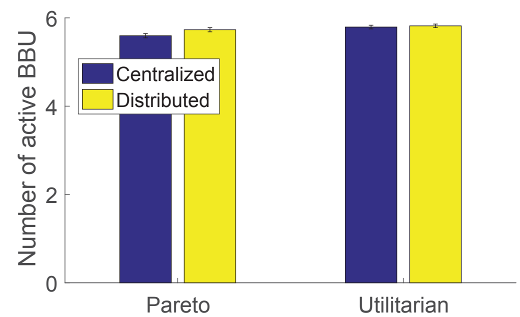
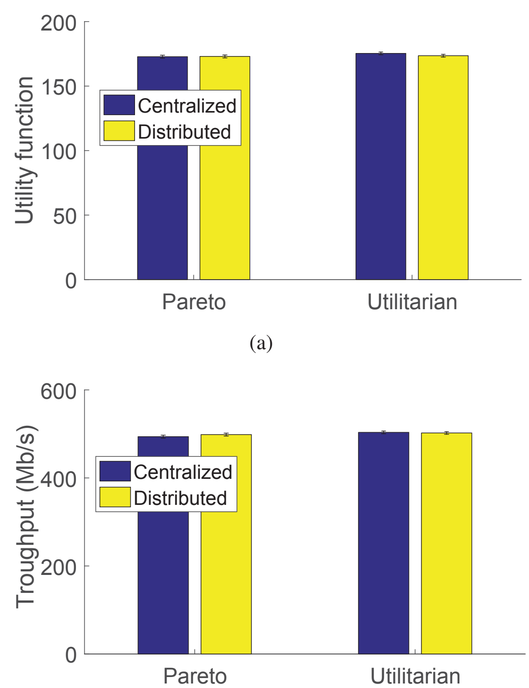


Fig. 9. Number of active BBUs: centralized vs. distributed approaches



(b)

Fig. 10. Utility function and throughput: centralized vs. distributed approaches

2) Convergence time: the main advantage of the distributed approaches over the centralized approaches appears in

the number of iterations necessary to reach final solutions. While centralized approaches iterate over all possible partitions given by the Bell number (877 possible partitions in our case) to form clusters, distributed approaches converge in a maximum of 11 iterations as illustrated in Fig. 11. More importantly, distributed approaches provide close performances to the centralized ones, as discussed earlier. Note that in our distributed algorithm, we neglected the signaling delay between RRHs.

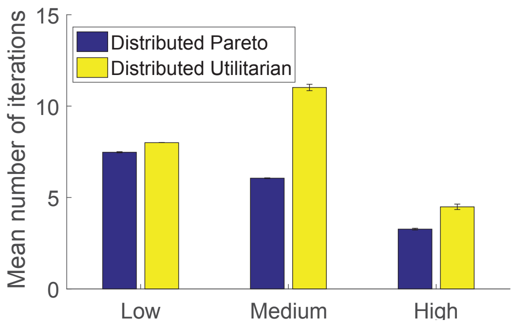


Fig. 11. Number of iterations in our distributed coalition formation approach

VII. Conclusion

In this paper, we have addressed the RRH clustering in cloud radio access networks and formulated it as a coalition formation game. RRHs collaborate and organize themselves into disjoint independent clusters, in a way to maximize network utility. This function reflects network performance, more precisely throughput and handover frequency, as well as network power consumption. Optimal centralized approaches using the Pareto order and the Utilitarian order were derived based on exhaustive search. However, forming clusters was computationally intensive. Therefore, we have introduced distributed approaches based on the merge-and-split rule and proved its efficiency for implementation in practice. While the number of iterations needed to form clusters is drastically reduced, distributed approaches achieve very close performances to the centralized approaches. For future work, we propose to integrate the inter-cluster interferences in the utility function and study their impact on the RRH clustering.

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