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A Hybrid Approach for RRH Clustering in Cloud Radio Access Networks based on Game Theory

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ABSTRACT

Cloud Radio Access Networks (C-RAN) is an evolution in the base station architecture, mainly composed of two elements: The Base Band Unit (BBU) and the Remote Radio Head (RRH). The BBU is a centralized pool of computational resources to provide the signal processing and coordination functionality required by all cells, while the RRHs are light radio units that User Equipment (UE) connects to via the RAN. Many advantages are derived from this architecture, such as dynamic BBU-RRH associations and statistical multiplexing gains. In particular, the BBU-RRH association problem is crucial for reducing power consumption. In this paper, we focus on decentralized BBU-RRH association, which has not received attention in the literature. Therefore, the aim of this work is to propose a hybrid two-stage approach that includes a game theoretic framework for the BBU-RRH association, and a centralized scheme to set the adequate number of available BBUs. The game among RRHs is solved by two different algorithms. The first relies on the best response algorithm, namely H-BR-IACA. The second is based on a reinforcement learning method (the replicator dynamics), namely H-DR-IACA. We compare our devised solution to a centralized approach proposed in a previous work. The results of our proposition show close performance to the centralized method.

CCS CONCEPTS

• **Networks** → **Mobile networks**; *Wireless access points, base stations and infrastructure*;

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KEYWORDS

Cloud Radio Access Networks, RRH clustering, power saving, game theory, best response, reinforcement learning

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1 INTRODUCTION

Wireless communications have seen a tremendous growth in traffic demand and a rapid evolution of technology. Hence, there is an increasing challenge in the operation of the upcoming 5G networks: huge amounts of data are becoming an overwhelming part of the traffic, while the associated income is shrinking. Similarly, both the energy consumed and interference levels are growing rapidly due to aggressive spectrum allocation in such dense networks. Finally, such densification leads to an imbalance in resource consumption due to the disparity of the mobile traffic across the network. To meet these challenges, a promising approach toward such 5G networks is to introduce cloud-based radio access networks (C-RAN). Unlike conventional RANs, a C-RAN decouples the baseband processing unit (BBU) from the remote radio head (RRH), allowing for centralized operation of BBUs and scalable deployment of lightweight RRHs. Unlike in conventional architecture, many RRHs are clustered to a single BBU when traffic load is low, resulting in power consumption reduction and increased energy efficiency. In addition, when RRHs are clustered together, they logically form a single cell and act as a distributed antenna system. Thus, the intra-cluster interference is canceled and the spectral efficiency is enhanced.

However, the challenge is to design a suitable logical mapping between each RRH and one or multiple managing BBUs, called BBU-RRH association. This design should be performed carefully so as to optimize the resource allocation, taking into account the

load balancing factor of served cells and the intra-cluster interference cancellation among RRHs associated to the same BBU. In this paper, we put forward a hybrid approach where a central controller decides the number of available BBUs, while the RRHs choose in a distributed fashion to join a given BBU in a way to minimize their own cost.

2 RELATED WORK

There are several papers addressing the BBU-RRH association problem (also known as RRH clustering problem), with a common purpose of power consumption reduction. In [7], authors formulate the clustering problem as a coalition game, where RRHs organize themselves into clusters in order to increase a suitable utility function. In [9] and [2], authors propose a bin packing formulation for the RRH clustering problem. Authors in [3] propose a centralized approach for the BBU-RRH association problem. They suggest to switch the RRHs of a crowded BBU to a less loaded neighboring BBU.

While all those papers show significant improvement in terms of power saving, they ignore the inter-cluster interference. Unlike the previous references, the work in [1] shows that interference-aware decisions lead to optimized clusters of RRHs and enhance the power saving metric. The authors of the paper propose a Set Partitioning Problem formulation (SPP) and prove that the chosen subsets of RRHs are energy efficient, reducing the level of interference in the network. However, the work in [1] is a centralized formulation that requires significant signaling information concerning network load conditions and interference levels. This would lead to a huge burden in terms of signaling load over the fronthaul between BBUs and RRHs. The aim of this paper is to introduce a load balancing and interference-aware hybrid clustering scheme that operates in two stages. The main objective is to minimize the network power consumption (*i.e.*, minimize the number of active BBUs), while guaranteeing minimum throughput requirements for UEs. Moreover, our solution provides close performances to the centralized proposition of [1], with significant reduced signaling load. To the best of our knowledge, this is the first paper to propose a game theoretic framework for the BBU-RRH association problem that is solved into two different algorithms: The first relies on the best response algorithm [8]. The second is based on a reinforcement learning algorithm, namely the replicator dynamics [6].

The rest of the paper is organized as follows: Section 3 describes the system model. Section 4 puts forward our hybrid load balancing and interference-aware clustering problem. Performance evaluations are displayed in section 5. Section 6 concludes the paper.

3 SYSTEM MODEL

3.1 Network Topology

Our topology consists in a cellular network composed of R RRHs. Let \mathcal{R} be the set of RRHs. It is defined as $\mathcal{R} = \{1, \dots, r, \dots, R\}$. We define the set of clusters (*i.e.*, subsets of \mathcal{R}) as $\mathcal{C} = \{1, \dots, s, \dots, S\}$. We also define a partition $\mathcal{P} \subset \mathcal{C}$ of \mathcal{R} such as $s \cap s' = \emptyset \forall s, s' \in \mathcal{P}$, $s \neq s'$ and $\bigcup_{s \in \mathcal{P}} s = \mathcal{R}$.

3.1.1 Area Decomposition. Clustering decisions are based on long-term measurements. It is costly to consider decisions based on

time granularity of seconds or even milliseconds, because BBU-RRH association decisions require reconfigurations of the optical fronthaul connections. In addition, the traffic pattern changes at a scale of minutes. Thus, we consider input parameters based on average metrics, such as average radio conditions and average number of UEs. Precisely, the covered area is meshed into several discrete zones. Each zone is assimilated to a single test point, where a cumulative rate is generated from all UEs located in the same zone. We consider a quadratic meshing of the area and we calculate the average distance (D_{avr}) between any zone of index z and a RRH of index r . The calculation of D_{avr} and the UE association scheme are detailed in [1].

3.2 Cluster Rate Model

We assume that a Transmission Point Selection Technique (TPS) is applied in each BBU (*i.e.*, cluster). Consequently, the corresponding data is transmitted from a single RRH at a time and the interfering signals result in from the inter-cluster interferences. The $SINR_{z,r,s}$ ratio of zone z , served by RRH r , associated to cluster s would be expressed as:

$$SINR_{z,r,s} = \frac{P_r \cdot G_{z,r}}{N_0 + \sum_{\substack{r' \neq r \\ r' \in s' \neq s}} P_{r'} \cdot G_{z,r'}}, \quad (1)$$

where P_r and $P_{r'}$ denote the power emitted by RRHs r and r' respectively. $G_{z,r}$ and $G_{z,r'}$ are the channel gain between zone z and r , r' respectively. N_0 represents the thermal noise power and finally s and s' the clusters that RRHs r and r' belong to respectively.

The peak throughput of a UE located in zone z , served by RRH r that is associated to cluster s is expressed as $\chi_{z,r,s} = BW \cdot \log_2(1 + SINR_{z,r,s})$, where BW is the total bandwidth within a BBU.

Assuming a fair resource sharing model between n_s UEs, sharing the resources of cluster s , and a full buffer traffic model, the throughput perceived by a UE belonging to zone z of RRH r , associated to cluster s is $\frac{1}{n_s} \cdot \chi_{z,r,s}$. Consequently, if $n_{z,r}$ UEs (among n_s) are located in zone z , the cumulative throughput within such zone is expressed as $T(z, r, s) = \frac{n_{z,r} \cdot \chi_{z,r,s}}{n_s}$. The cumulative throughput derived in RRH r that is associated to cluster s is expressed as $T(r, s) = \sum_{z=1}^Z T(z, r, s)$, where Z is the total number of zones belonging to RRH r .

The cumulative throughput in cluster s (*i.e.*, BBU s) is expressed as $T(s) = \sum_{r=1}^R y_{r,s} \cdot T(r, s)$, where R is the total number of RRHs in the network, and $y_{r,s}$ denotes a binary variable defined as:

$$\begin{cases} y_{r,s} = 1, & \text{if } r \text{ is associated to } s \\ y_{r,s} = 0, & \text{otherwise} \end{cases} \quad (2)$$

3.3 BBU Power Consumption Model

We assume a linear power consumption for the BBU, as a function of the cumulative rate of cluster s [10]. It is expressed as $P(s) = A + B \cdot T(s)$, where $P(s)$ denotes the power consumed by an active BBU, A is the minimum power consumption of an active BBU at zero load and B is the coefficient variation of $P(s)$ as a function of $T(s)$ which is the cumulative throughput in cluster s as previously defined.

4 HYBRID CLUSTERING BASED ON GAME THEORY

Our hybrid proposition operates in two stages described in paragraphs 4.1 and 4.2. Initially, a central controller sets the number of BBUs made available to the RRHs. In the first stage, the distributed BBU-RRH association is portrayed as a potential game among competing RRHs to choose a suitable BBU. When the Nash Equilibrium [5] is attained, the second stage is reached, where the number of available BBUs can be modified. The two stages are iteratively executed until the right number of active BBUs is decided.

4.1 Non-Cooperative Game for BBU-RRH Association

Non-cooperative game theory models the interactions between players competing for a common resource. Hence, it is well adapted to RRH clustering. We define a multi-player game \mathcal{G} between the R RRHs.

We present the general framework of game $G = (\mathcal{R}, \mathcal{S}, C)$ that can be described as follows: The set \mathcal{R} of RRHs is the set of players. The set \mathcal{P} of available BBUs. An action of a RRH is selecting one of the available BBUs. The strategy of RRH r is denoted by the vector y_r whose components are $y_{r,s}$ defined in (2). Hence, $\mathbf{y} = (y_r)_{r \in \mathcal{R}} \in \mathcal{S}$ is a pure strategy profile, and $\mathcal{S} = S_1 \times S_2 \times \dots \times S_R$ is the space of all profiles. The set of cost functions $C = \{C_1, C_2, \dots, C_R\}$ that quantify the players' preferences over the possible outcomes of the game. Outcomes are determined by the particular action chosen by RRH r and the particular actions chosen by all other players.

4.1.1 Cost function. Each RRH seeks to minimize its own load balancing and interference-aware cost function by choosing an adequate strategy (i.e. BBU s). The cost function of RRH r is given by what follows:

$$C_r(y_r, y_{-r}) = \sum_{s \in \mathcal{P}} y_{r,s} \cdot \left[\underbrace{\alpha \cdot \alpha' \cdot \sum_{r' \neq r} y_{r',s}}_{\text{Term 1}} + \underbrace{\beta \cdot \beta' \cdot \left(\sum_{r' \neq r} G_{r',r} \cdot (1 - y_{r',s}) + N_0 \right)}_{\text{Term 2}} \right], \quad (3)$$

where $G_{r,r'}$ is the channel gain between RRHs r and r' , and $y_{r,s}$ is the binary variable defined as in (2).

The cost sustained by a given RRH r in any selected BBU depends upon the congestion impact inflicted by other RRHs $r' \in \mathcal{S}$ sharing the same radio resources of the common BBU s . The latter is depicted by Term 1 in (3) and acts as a load balancing function among active BBUs. Furthermore, the cost function should encompass the interference impact. Accordingly, Term 2 reflects the inter-cluster interference which is cancelled between RRH r and other RRHs that have chosen the same strategy (equivalently BBU) s . α and β are the weighting factors. We note that $\alpha + \beta = 1$ and α', β' are the normalization factors.

4.1.2 Attaining Pure Nash Equilibriums. In a non-cooperative game, a solution is obtained when all players adhere to a Nash Equilibrium (NE). A NE is a profile of strategies in which no player will profit from deviating its strategy unilaterally. Hence, it is a strategy profile

where each player's strategy is an optimal response to the other players' strategies.

Our game \mathcal{G} is a finite game and in general such games are not guaranteed to have Pure NEs (PNEs). However, for our game an exact potential function [4] exists, which means that the unilateral change of one RRH strategy y_r to y'_r results in a change of its cost function that is equal to the change of a so-called potential function $\phi : \mathcal{S}^R \rightarrow \mathbb{R}$.

An example of such a potential function is given by the following:

$$\phi(\mathbf{y}) = \sum_{s \in \mathcal{P}} \sum_{r \in \mathcal{R}} y_{r,s} \left(\frac{1}{2} \cdot \sum_{r' \neq r} y_{r',s} + y_{r,s} + \frac{1}{2} \cdot \sum_{r' \neq r} (2 - y_{r',s}) G_{r',r} + N_0 \right), \quad (4)$$

Furthermore, such games have the appealing property of converging to PNE. In our work, we apply two different algorithms to solve the game. The first is the best response, which guarantees the convergence to PNE. The second is based on a reinforcement learning algorithm, namely replicator dynamics, that converges to PNE for exact potential games:

- *Best response algorithm:* At each round of the best response algorithm, a RRH chooses the BBU that provides it the lowest cost (3). Convergence is attained when all RRHs choose the same strategies as in the previous round.
- *Replicator dynamics algorithm:* We denote by $p_{r \in \mathcal{R}}(t)$ the vector of mixed strategies whose components are $p_r^s(t)$, defining the probability that RRH r chooses BBU s at iteration t . At each t , a RRH selects a BBU according to the distribution probability $p_{r \in \mathcal{R}}(t)$ and receives a cost. The vector $p_{r \in \mathcal{R}}(t)$ is updated accordingly and the process is repeated until the PNE is learned.

4.2 Centralized BBU Activation/Deactivation

The second stage of the algorithm decides whether to activate or to deactivate a BBU. Precisely, this stage consists in examining the lowest throughput per UE among all clusters and verifies if constraints (5) are respected or not:

$$T(s) \geq n_s \cdot D_{min}, \forall s \in \mathcal{P} \quad (5)$$

Constraints (5) state that the throughput per UE should stay greater than a minimal threshold, denoted by D_{min} . If not, the algorithm increases by one the number of available BBUs, and re-launches the BBU-RRH association game of the first stage. However, to reduce power consumption, when the lowest throughput per UE respects (5), the algorithm decreases the number of active BBUs and falls back to the first stage. When the algorithm decides to deactivate a BBU and reactivate it again, it stops running and outputs a solution. More precisely, when the algorithm deactivates a BBU and realizes that constraints (5) are not respected, it falls back to the previous number of active BBUs (before the deactivation) and sets back the previous BBU-RRH associations. In this work, the central controller starts from a random number of active BBUs.

5 PERFORMANCE EVALUATION

In this section, we provide a comparative study between our hybrid schemes (H-BR-IACA and H-DR-IACA), the No Clustering scheme, where a BBU is entirely dedicated to a single RRH, and finally a centralized scheme proposed in a previous work [1] deemed C-IACA.

5.1 Simulation Results

We use Matlab for simulations, and we consider a network composed from seven cells. As previously mentioned, the area is meshed into several quadratic zones. We consider a uniform UEs distribution in each cell. In other terms, the number of UEs per cell is the same in each zone associated to the cell. We set the weights α and β of the cost function to 0.75 and 0.25 respectively (cf. equation (7)).

The simulation parameters are shown in table 1.

Table 1: Simulation parameters

Parameter	Value
Propagation Model	Cost Hata 231
Shadowing Standard Deviation	10 dB
Transmit Power of RRH	40 dBm
Thermal Noise Power	-174 dBm/Hz
BW	10 MHz
Cell Radius	500 m
A	50 W
B	0.6
D_{min}	2 Mb/s

5.1.1 The C-IACA vs. H-BR-IACA vs. H-DR-IACA vs. No Clustering scheme. We start by providing the first performance metric given in Figure 1. It represents the number of active BBUs as a function of the number of UEs per cell. For 1 to 4 UEs per cell, the C-IACA and the hybrid schemes activate only one BBU. When the number of UEs per cell reaches 5, more BBUs are activated. All of the C-IACA, H-BR-IACA and H-DR-IACA provide the same number of active BBUs except for 9 and 10 UEs per cell, where the H-BR-IACA scheme activates an additional BBU in comparison with the centralized scheme for 9 UEs per cell, and the H-DR-IACA scheme activates a slightly higher number of BBUs for 10 UEs per cell in comparison to the C-IACA and H-BR-IACA schemes. The No Clustering scheme activates all available BBUs whatever the number of UEs per cell is.

Figure 2 displays the power saving metric as a function of the number of UEs per cell. Between 1 and 4 UEs per cell, we notice the highest power savings for the C-IACA and the hybrid schemes. Almost same power economies are realized in all schemes, except for 9 and 10 UEs per cell, where additional BBUs are activated by the hybrid schemes in comparison to the C-IACA as shown in Figure 1. Further, no power economy is achieved when the number of UEs per cell exceeds 11, as all BBUs are activated.

Figure 3 shows the mean throughput per UE as a function of the number of UEs per cell, given as the total realized throughput within the system over the total number of UEs. The highest values are attained through the No Clustering scheme owing to the full buffer traffic model. However, we notice that all of the centralized

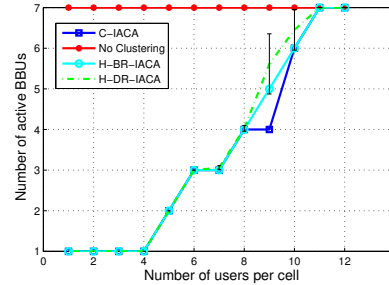


Figure 1: Number of active BBUs: C-IACA vs. H-BR-IACA vs. H-DR-IACA vs. No Clustering

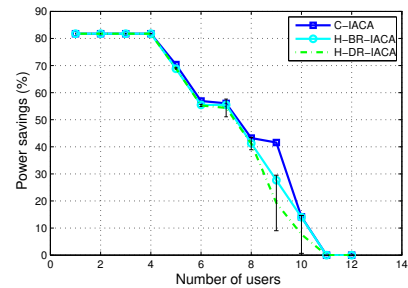


Figure 2: Power saving: C-IACA vs. H-BR-IACA vs. H-DR-IACA

and hybrid schemes realize much more power economy at the cost of lower mean throughput per UE. In addition, the C-IACA and the hybrid schemes guarantee the targeted QoS for UEs, and do not offer throughputs less than $D_{min} = 2$ Mb/s. For high number of UEs per cell, the mean throughput per UE is reduced for all schemes due to scarcity in radio resources.

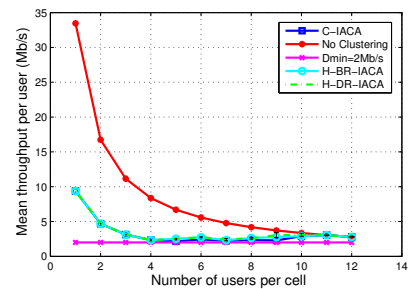


Figure 3: Mean throughput per user: C-IACA vs. H-BR-IACA vs. H-DR-IACA vs. No Clustering

Figure 4 represents the execution time of all the clustering schemes as a function of the number of UEs per cell. We note that the algorithms are executed over a hardware of 64-bit, Intel 7 core, 2.5 Ghz. We notice that the H-BR-IACA scheme consumes less computational time for all load conditions in comparison to other schemes. The H-DR-IACA scheme consumes less computational time than

the C-IACA scheme for a number of UEs per cell that varies between 1 and 7. When the number of UEs per cell is greater than 7, the computational time of the H-DR-IACA scheme is greater than all other schemes. In fact, when a higher number of choices (*i.e.*, number of BBUs) is attributed to the reinforcement learning algorithm (H-DR-LIACA), the time to convergence would be greater. However, reinforcement learning algorithms require much less amount of signaling load information.

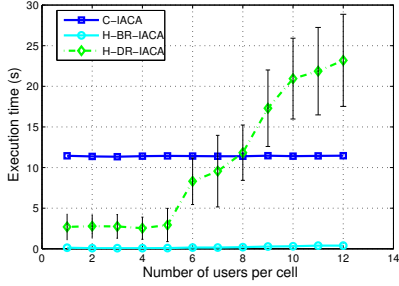


Figure 4: Execution time: C-IACA vs. H-BR-IACA vs. H-DR-IACA

6 CONCLUSION

In this paper, we formulate a hybrid proposition for the RRH clustering problem comprising a centralized scheme and a non-cooperative game. The non-cooperative game is solved in two different manners. The first relies on the best response dynamics, whereas the second is a reinforcement based learning algorithm. We compare our devised schemes to an existing centralized approach based on SPP. The results show that our hybrid scheme realizes close performance to the centralized solution. In future work, we intend on submitting our schemes to the stringency of a real case topology with twenty cells.

APPENDIX

We prove hereafter that the game at hand is an exact potential game. We simply need to show that if \mathbf{y} and \mathbf{y}' are two profiles which only differ in the strategy of one RRH r , then:

$$C_r(\mathbf{y}_r, \mathbf{y}_{-r}) - C_r(\mathbf{y}'_r, \mathbf{y}_{-r}) = \phi(\mathbf{y}_r, \mathbf{y}_{-r}) - \phi(\mathbf{y}'_r, \mathbf{y}_{-r}) \quad (6)$$

We begin by computing $C_r(\mathbf{y}_r, \mathbf{y}_{-r}) - C_r(\mathbf{y}'_r, \mathbf{y}_{-r}) =$

$$\begin{aligned} & \sum_{s \in \mathcal{S}} y_{r,s} \cdot [\alpha \alpha' \cdot (\sum_{r' \neq r} y_{r',s} + y_{r,s}) \\ & + \beta \beta' \cdot (\sum_{r' \neq r} G_{r',r} (1 - y_{r',s}) + N_0)] \\ & - \sum_{s \in \mathcal{S}} y'_{r,s} \cdot [\alpha \alpha' \cdot (\sum_{r' \neq r} y_{r',s} + y'_{r,s}) \\ & + \beta \beta' \cdot (\sum_{r' \neq r} G_{r',r} (1 - y_{r',s}) + N_0)] \\ & = \sum_s (y_{r,s} - y'_{r,s}) \cdot [\alpha \alpha' \cdot (\sum_{r' \neq r} y_{r',s} + y_{r,s} + y'_{r,s}) \\ & + \beta \beta' \cdot (\sum_{r' \neq r} G_{r',r} (1 - y_{r',s}) + N_0)] \end{aligned} \quad (7)$$

Then, we compute $\phi(\mathbf{y}_r, \mathbf{y}_{-r}) - \phi(\mathbf{y}'_r, \mathbf{y}_{-r}) =$

$$\begin{aligned} & \sum_{r' \neq r} \sum_s y_{r',s} (\alpha \alpha' \cdot (\frac{1}{2} \cdot \sum_{r' \neq r} y_{r',s} + y_{r,s}) + \beta \beta' \cdot (\frac{1}{2} \cdot \\ & \sum_{r' \neq r} (2 - y_{r',s}) G_{r',r} + N_0)) \\ & - \sum_{r' \neq r} \sum_s y'_{r',s} (\alpha \alpha' \cdot (\frac{1}{2} \cdot \sum_{r' \neq r} y'_{r',s} + y'_{r,s}) + \beta \beta' \cdot (\frac{1}{2} \cdot \\ & \sum_{r' \neq r} (2 - y'_{r',s}) \cdot G_{r',r} + N_0)) \\ & + \sum_s (y_{r,s} - y'_{r,s}) \cdot [\alpha \alpha' \cdot (\frac{1}{2} \cdot \sum_{j \neq r} y_{j,s} + (y_{r,s} + y'_{r,s})) + \\ & \beta \beta' \cdot (\frac{1}{2} \cdot \sum_{j \neq r} (2 - y_{j,s}) G_{j,r} + N_0)] \\ & = \sum_s (y_{r,s} - y'_{r,s}) \cdot (\alpha \alpha' \cdot \frac{1}{2} \cdot \sum_{r' \neq r} y_{r',s} - \frac{1}{2} \cdot \beta \beta') \\ & \sum_s (y_{r,s} - y'_{r,s}) \cdot (\sum_{r' \neq r} y_{r',s} \cdot G_{r',r}) \\ & + \sum_s (y_{r,s} - y'_{r,s}) \cdot [\alpha \alpha' \cdot (\frac{1}{2} \cdot \sum_{r' \neq r} y_{r',s} + (y_{r,s} + y'_{r,s})) + \\ & \beta \beta' \cdot (\frac{1}{2} \cdot \sum_{r' \neq r} G_{r',r} (2 - y_{r',s}) + N_0)] \\ & = \sum_s (y_{r,s} - y'_{r,s}) \cdot [\alpha \alpha' \cdot (\sum_{r' \neq r} y_{r',s} + (y_{r,s} + y'_{r,s})) + \\ & \beta \beta' \cdot (\sum_{r' \neq r} G_{r',r} (1 - y_{r',s}) + N_0)] \end{aligned} \quad (8)$$

As $G_{r,r'} = G_{r',r}$ (impact of RRH r on RRH r' is the same as impact of RRH r' on r), we have indeed:

$$C_r(\mathbf{y}_r, \mathbf{y}_{-r}) - C_r(\mathbf{y}'_r, \mathbf{y}_{-r}) = \phi(\mathbf{y}_r, \mathbf{y}_{-r}) - \phi(\mathbf{y}'_r, \mathbf{y}_{-r}).$$

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