

Power-Efficient Resource Allocation in C-RANs With SINR Constraints and Deadlines

Salvatore D'Oro , Marcelo Antonio Marotta, Cristiano Bonato Both, Luiz DaSilva , and Sergio Palazzo 

Abstract—In this paper, we address the problem of power-efficient resource management in Cloud Radio Access Networks (C-RANs). Specifically, we consider the case where Remote Radio Heads perform data transmission, and signal processing is executed in a virtually centralized Base-Band Units pool. Users request to transmit at different time instants; they demand minimum signal-to-noise-plus-interference ratio (SINR) guarantees, and their requests must be accommodated within a given deadline. These constraints pose significant challenges to the management of C-RANs and, as we will show, considerably impact the allocation of processing and radio resources in the network. Accordingly, we analyze the power consumption of the C-RAN system, and we formulate the power consumption minimization problem as a weighted joint scheduling of processing and power allocation problem for C-RANs with minimum SINR and finite horizon constraints. The problem is a Mixed Integer Non-Linear Program, and we propose an optimal offline solution based on Dynamic Programming. We show that the optimal solution is of exponential complexity; thus, we propose a sub-optimal greedy online algorithm of polynomial complexity. We assess the performance of the two proposed solutions through extensive numerical results. Our solution aims to reach an appropriate tradeoff between minimizing the power consumption and maximizing the percentage of satisfied users. We show that it results in power consumption that is only marginally higher than the optimum, at significantly lower complexity.

Index Terms—Cloud Radio Access Networks, resource allocation, energy efficiency.

I. INTRODUCTION

CLOUD Radio Access Networks (C-RANs) are expected to provide unprecedented scalable, flexible, and efficient infrastructure provisioning and management in future 5G networks and beyond [1]–[3]. In Cloud Radio Access Networks (C-RANs), a set of Remote Radio Heads (RRHs) perform radio transmissions, while signal processing, e.g., base band process-

ing, is executed in a pool of one or more Base Band Units (BBUs) as a cloud system [4]–[6]. RRHs and BBUs are interconnected through high-speed optical fiber links, which makes it possible to meet the high-performance requirements of 5G networks, thus guaranteeing low latency and high-rate data transmission [7].

C-RANs can achieve a considerable reduction of both CAPEX and OPEX while providing efficient and smart management of network resources. Since the signal processing is performed in the BBU pool, the RRHs are characterized by a simple transceiver design. In addition, by exploiting the centralized architecture of the BBU pool, it is possible to perform advanced and efficient signal processing techniques that require coordination. For example, Coordinated Multipoint (CoMP) and Joint Transmission (JT) can be implemented to reduce interference and improve the spectral efficiency of the system. To process a given user transmission in C-RAN environments, the system: i) allocates the user to the available downlink channels; ii) selects the subset of active RRHs which will transmit to the corresponding user, and determines the transmission power level of those RRHs; and iii) runs a Virtual Function (VF) [8], or creates a Virtual Machine (VM) [9] instance in the BBU pool, to which a given amount of computational resources is assigned. In the remainder of this paper, we do not distinguish between virtual functions and virtual machines, and we refer to both of them as VMs.

To take full advantage of C-RANs, green and lightweight management of network resources has to be considered [10]. However, C-RANs comprise heterogeneous network elements, which makes the design of energy-efficient algorithms a challenging task. As an example, to minimize the power consumption of the whole C-RAN system, both radio and computational resources must be managed jointly. That is, the activation and management of RRHs have to be addressed together with the efficient allocation of the computational resources in the BBU pool. This problem is not trivial, and it is further exacerbated when minimum Quality of Service (QoS) requirements, such as temporal deadlines and Signal-to-interference-plus-noise ratio (SINR), are considered [11]. Due to its complexity and importance, many solutions to the green management of C-RANs have been proposed in the literature [9], [12]–[20]. However, those solutions have not been designed to deal with the relevant case of finite-horizon scheduling problems. Thus, they are expected to be sub-optimal when user transmission requests dynamically arrive at different time instants and have to be accommodated within a given deadline.

Manuscript received June 20, 2018; revised December 3, 2018 and March 21, 2019; accepted April 21, 2019. Date of publication April 25, 2019; date of current version June 18, 2019. This work was supported in part by the Science Foundation Ireland under Grant 13/RC/2077 and in part by the SFI Research Centre CONNECT. The review of this paper was coordinated by Prof. X. Wang. (Corresponding author: Salvatore D'Oro.)

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Digital Object Identifier 10.1109/TVT.2019.2913310

In this paper, we design an optimal green mechanism for such a dynamic scenario. Specifically, we analyze the case where subscribers dynamically submit transmission requests, coupled with the corresponding requirements regarding minimum average SINR and a delivery deadline. We formulate the power consumption minimization problem for C-RANs as a weighted joint power allocation and user scheduling problem. By considering that the BBU pool has limited computational resources, we account for both temporal and SINR constraints, and we show that the problem can be formalized as a Mixed Integer Non-Linear Problem (MINLP). For such a problem, we provide an optimal offline solution based on Dynamic Programming (DP) techniques. We show that its computational complexity is exponential, which makes it unfeasible to obtain an optimal solution in large-scale and dense networks within a reasonable amount of time. Accordingly, we design a greedy online algorithm of polynomial computational complexity. We assess and compare the performance of the two proposed solutions through extensive numerical results. Our solution aims to reach an appropriate trade-off between minimizing the power consumption and maximizing the percentage of satisfied users. Our proposed algorithm results in power consumption that is only marginally higher than the optimum, at significantly lower complexity.

The remainder of this paper is organized as follows. Related work is presented in Section II. Section III illustrates the considered C-RAN, and the corresponding power consumption analysis. The weighted joint power allocation and user scheduling are formulated in Section IV. Section V provides the optimal offline solution to the problem. A sub-optimal online solution with polynomial complexity is proposed in Section VI. Numerical results are presented in Section VII. Finally, in Section VIII we outline our main conclusions.

II. RELATED WORK

The problem of providing power-efficient 5G systems under QoS constraints through joint user transmission scheduling and power allocation has been extensively addressed in the literature. As an example, the downlink joint power and wireless resource allocation problem in C-RANs under minimum SINR constraints has been considered in [12]–[16]. In [9], a cross-layer approach for the power-efficient allocation of network resources is considered where both the RRHs and the BBU pool are assumed to have limited computational and hardware resources. The same problem is also addressed and solved in [17] where, instead, a requirement on the desired task completion time is considered. A different approach is contemplated in [18], where power control and caching at the RRHs are exploited to provide mobile users with minimum QoS guarantees. In contrast, a fractional programming approach is proposed in [19] to maximize the energy efficiency of the network. Those works focus on minimizing the actual overall power consumption of the network. However, it is worth noting that the consumed power of each network element can be significantly different. As an example, the power needed to activate the optical fibers between the BBU pool and the RRHs can be significantly lower than the power needed to activate

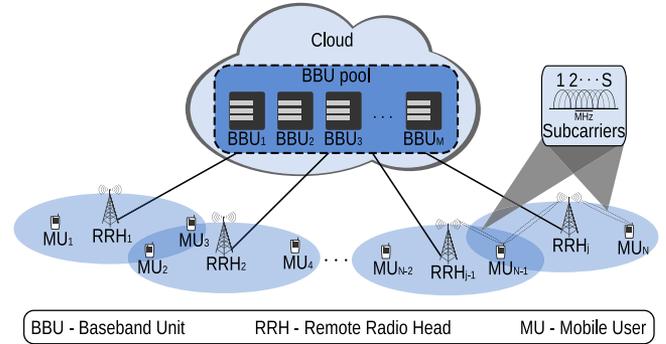


Fig. 1. The considered C-RAN scenario.

the RRHs [20]. Accordingly, a more general approach consists in the minimization of a weighted version of the actual power consumption. Such an approach is considered in [21], where the weighted power consumption of the network is minimized by jointly addressing the power and resource allocation problems for both downlink and uplink communications.

Though optimal, most of the above solutions do not consider limited computational resources at the BBU pool. Furthermore, they have not been designed to deal with finite-horizon scheduling problems, where user transmission requests dynamically arrive and have to be scheduled within a deadline. The scheduling problem for C-RANs over a finite horizon has been considered in [22], [23]. However, the solution in [22] only focuses on the BBU pool and does not consider the power consumption of the RRHs, while [23] does not account for CoMP transmissions, and the power consumption is restricted to the transmission power only.

The above literature review reveals that the problem of minimizing the power consumption of C-RANs over a finite-horizon through joint RRH and BBU management is worth investigating. It also shows that further efforts are needed, as none of the above solutions can be readily applied to optimally solve the finite-horizon power minimization problem we consider in this paper.

III. SYSTEM MODEL

We study a C-RAN scenario where mobile users access the network using several RRHs which are connected to a BBU pool through high-speed optical links, as shown in Fig. 1. We consider a time slotted multi-carrier (or multi-frequency) system where a set \mathcal{S} of subcarriers are available for data transmission. In this work, we focus on the downlink communications between RRHs and mobile users. We assume that the allocation of downlink resources has to be performed over a finite horizon. The finite-horizon concept captures time requirements in those scenarios where channel gain coefficients or user positions change every T slots (e.g., slow-fading or block-fading scenarios). Let $\mathcal{T} = \{1, 2, \dots, T\}$ denote the set of time slots within the horizon.

A. Modeling Mobile Users

Let \mathcal{N} be the set of mobile users in the network. One or more RRHs can serve each user $n \in \mathcal{N}$. In the following, we assume

that mobile users are equipped with single-antenna transceivers, which at any given time instant can only receive signals on a single subcarrier.

Each user transceiver generates one (or more) request-to-transmit to the Telecommunications Operator (TO). Specifically, each request contains the following parameters:

- *Requesting User*: it is the mobile user n who sends the request $r \in \mathcal{R}_n$.
- *Deadline*: mobile users' requests have to be accommodated by 1) instantiating a VM in the BBU pool to process user signals; and 2) scheduling downlink transmissions through one (or more) RRHs for the whole duration of a time slot [9] within a given *temporal window*. For each request, the temporal window is defined by the 2-tuple (t_r^0, δ_r) , where t_r^0 represents the arrival time slot of the request, and δ_r is the duration of the temporal window within which the request must be accommodated.
- *SINR Constraint*: it represents the minimum average SINR level γ_r that has to be guaranteed to request r .
- *Computational Resources*: they represent the amount m_r of computational resources to run a VM in the BBU pool for request r . In general, the higher the value of γ_r , the higher the value of m_r , i.e., $m_r = f(\gamma_r)$ with $\partial f(\gamma_r)/\partial \gamma_r \geq 0$. Such an assumption stems from the evidence that large values of γ_r require the BBU pool to run more complex signal processing operations. Accordingly, m_r can be modeled as follows [24], [25]:

$$m_r = m_{VM} + \theta \log_2(1 + \gamma_r) \quad (1)$$

where m_{VM} is a constant term that represents the amount of resources needed to activate a VM and perform signal processing (e.g., modulation, encoding, Fast Fourier Transform, etc.), and $\theta > 0$ is a weighting parameter to vary the slope of the function m_r [25]. It is worth noting that (1) quantifies the amount of computational resources in the BBU pool to be allocated to a given request that demands a minimum SINR level γ_r . How to satisfy the aforementioned SINR requirement will be the main topic of Sections V and VI, where joint power and channel allocation is effectively used to satisfy users' requests while minimizing the power consumption of the system.

- *Channel State Information (CSI)*: at each time slot t , the channel is modeled through its *channel coefficient* $h_{rjs}(t)$, which represents the channel between the mobile user who has made the request r and the RRH j on subcarrier s at time slot t . For clarity of notation, we introduce the *channel gain coefficient* $g_{rjs} = |h_{rjs}|^2$. Accordingly, the CSI is represented by the channel gain coefficient matrix $\mathbf{G}_r(t) = (g_{rjs}(t))_{j \in \mathcal{H}, s \in \mathcal{S}, t \in \mathcal{T}}$. We assume block-fading, i.e., channel gain coefficients remain constant within each time slot t .

Without loss of generality, in the following we omit the time slot indicator t and we focus on the case where channel gain coefficients do not vary within the horizon, i.e., $g_{rjs}(t) = g_{rjs}(t') = g_{rjs}$ for all $t, t' \in \mathcal{T}$. However, the solutions proposed in this paper also apply to the more general

case where channel gain coefficients vary at each time slot. Accordingly, each request $r \in \mathcal{R}_n$ is defined by the 6-tuple $r = (n, t_r^0, \delta_r, \gamma_r, m_r, \mathbf{G}_r)$. Also, we assume that CSI information is always available to the system through pilot-based [26], [27] or statistical [28], [29] approaches. However, we do not make any assumption on the accuracy of the CSI estimation procedure.

B. Modeling RRHs

RRHs are equipped with multiple antennas and are capable of performing simultaneous transmissions on multiple subcarriers. However, due to hardware limitations, RRHs are required to satisfy a *power constraint*. Specifically, at each time slot t , the total transmission power for each RRH j has to be lower than or equal to an RRH-specific maximum transmission power level P_j . RRHs are connected to the BBU pool through high-speed optical fiber links.

C. Modeling the BBU Pool

The BBU pool is the centralized entity where signal processing is performed. Through centralized processing, it is possible to exploit advanced signal processing techniques such as CoMP and JT. Hence, to improve the SINR and reduce the interference with other mobile users connected to adjacent RRHs, in this work we exploit both techniques to provide JT-CoMP transmissions where several RRHs simultaneously transmit the same signal to a given user. When a given request is scheduled, a VM instance on the BBU pool is instantiated, and a given amount of computational resources in the pool is assigned to it. Specifically, for each request the system: 1) allocates a downlink time slot on a given subcarrier to the corresponding mobile user; 2) selects the subset of active RRHs which will transmit to the corresponding mobile user, and determines their optimal transmission power levels; and 3) creates a VM instance in the BBU pool. Also, we assume that the BBU pool has a limited amount M of computational resources.

D. Variables Definition

We hereby introduce the relevant variables in our model of the C-RAN scenario, which for the sake of clarity are also summarized in Table I. Let $\mathcal{R} = \bigcup_{n \in \mathcal{N}} \mathcal{R}_n$ be the set of all the requests sent by mobile users. To model the allocation of mobile users in the time and frequency domains, we define the *allocation variable* $a_{rs}(t) \in \{0, 1\}$, where $a_{rs}(t) = 1$ if request $r \in \mathcal{R}$ is allocated to sub-carrier $s \in \mathcal{S}$ at time slot t . Otherwise, $a_{rs}(t) = 0$. Let $\mathbf{a} = (\mathbf{a}(t))_{t \in \mathcal{T}}$, where $\mathbf{a}(t) = (a_{rs}(t))_{r \in \mathcal{R}, s \in \mathcal{S}}$. Furthermore, the transmission power of RRH j on subcarrier s at time slot t is defined as the continuous variable $p_{rjs}(t) \in [0, P_j]$. Let $\mathbf{p} = (\mathbf{p}(t))_{t \in \mathcal{T}}$, where $\mathbf{p}(t) = (p_{rjs}(t))_{r \in \mathcal{R}, j \in \mathcal{H}, s \in \mathcal{S}}$.

To model the selection (i.e., activation) of an RRH, we define the following *activation indicator* $y_j(t) \in \{0, 1\}$, where $y_j(t) = 1$ if RRH j is transmitting at time slot t . Otherwise, $y_j(t) = 0$. Let $\mathbf{y} = (\mathbf{y}(t))_{t \in \mathcal{T}}$, where $\mathbf{y}(t) = (y_j(t))_{j \in \mathcal{H}}$.

TABLE I
SUMMARY OF NOTATION

Variable	Description
$\mathcal{N}, \mathcal{H}, \mathcal{S}, \mathcal{R}$	Sets of users, RRHs, subcarriers and requests
P_j	Maximum transmission power level of an RRH
t_r^0, δ_r	Arrival time of a request and its deadline
m_r	Amount of computational resources to process a request
\mathbf{G}_r	Channel gain matrix
σ^2	Noise power on each subcarrier
T	Horizon duration
γ_r	Minimum average SINR requirement
$a_{rs}(t)$	Allocation variable
$y_j(t)$	Activation indicator
$p_{rjs}(t)$	Transmission power level
M	Computational resources of the BBU pool
$P_j^{(F)}, P_j^{(ON)}, P_j^{(sleep)}$	Fibers, activation and sleep power costs
$P^{(BBU)}(m)$	Consumed power by the BBU pool when m resources are allocated
$\mathcal{C}^{TX}, \mathcal{C}^A, \mathcal{C}^H$	Transmission, activation and total power costs
\mathcal{C}^B	Total processing power cost in the BBU pool
\mathcal{C}	Overall weighted power consumption of the network
ω_R, ω_B	Weighting parameters

Accordingly, for each $r \in \mathcal{R}$ and $s \in \mathcal{S}$, the average SINR can be written as follows:

$$\text{SINR}_{rs}(t) = \frac{\sum_{j \in \mathcal{H}} p_{rjs}(t) g_{rjs}}{\sigma^2 + \sum_{j \in \mathcal{H}} \sum_{r' \in \mathcal{R}, r' \neq r} p_{r'js}(t) g_{r'js}} \quad (2)$$

where σ^2 is the noise power on the considered subcarrier, and g_{rjs} is the expected channel gain coefficient *w.r.t.* the mobile user which requested r and the RRH j on subcarrier s .

E. Constraints Definition

Under the above assumptions, we define the following constraints:

- 1) *RRH power constraint*: for each activated $j \in \mathcal{H}$, the overall transmission power has to be lower than P_j . Thus,

$$\sum_{r \in \mathcal{R}} \sum_{s \in \mathcal{S}} p_{rjs}(t) \leq y_j(t) P_j, \quad \forall j \in \mathcal{H}, \forall t \in \mathcal{T} \quad (3)$$

- 2) *Scheduling constraints*: each mobile user has a single antenna, thus it can be scheduled to a single subcarrier. Also, its request has to be accommodated only once. Furthermore, a given request cannot be scheduled if its corresponding temporal requirement is not satisfied. That is,

$$\sum_{t=1}^T \sum_{s \in \mathcal{S}} a_{rs}(t) = 1, \quad \forall r \in \mathcal{R} \quad (4)$$

Furthermore, $a_{rs}(t) = 0$ and $p_{rjs}(t) = 0$ if $t \notin [t_r^0, t_r^0 + \delta_r]$.

- 3) *SINR constraint*: the average SINR for each scheduled mobile user defined in (2) has to be higher than the minimum QoS requirement γ_r

$$\text{SINR}_{rs}(t) \geq \gamma_r a_{rs}(t), \quad \forall s \in \mathcal{S}, \forall r \in \mathcal{R}, \forall t \in \mathcal{T} \quad (5)$$

- 4) *BBU bounded computation constraint*: the amount of computational resources in the BBU pool is, in general,

bounded. Let M be the maximum amount of computational resources which are available in the BBU pool. Accordingly, at each time slot t we have that the amount of resources allocated to requests in \mathcal{R} is bounded by M . From constraint (4), this constraint can be defined as follows:

$$\sum_{r \in \mathcal{R}} \sum_{s \in \mathcal{S}} m_r a_{rs}(t) \leq M, \quad \forall t \in \mathcal{T} \quad (6)$$

F. Power Consumption

In the considered scenario, the main sources of power consumption can be summarized as follows:

- *RRH Transmission and Activation*: at the RRH side, there are three main power-consuming processes. First, each RRH that has been selected for data transmission has to be turned on. Accordingly, there is an *activation power cost* equal to $P_j^{(ON)}$. Second, when an RRH is turned on, it is also connected to the BBU pool through optical fibers, which generates a *fiber power cost* equal to $P_j^{(F)}$. Note that $P_j^{(F)}$ depends on j as RRHs are located at different distances from the BBU pool. RRHs which are far away from the BBU require optical amplifiers, additional connectors and fibers. Therefore, their $P_j^{(F)}$ will be larger, while nearer RRHs will have a small $P_j^{(F)}$. The third process is represented by the transmission power levels $p_{rjs}(t)$. It is worth mentioning that the switch between on/off states would be too costly at small time-scales (e.g., data frame scale). In fact, RRHs can not be instantaneously turned on due to hardware constants, which eventually results in processing and transmission latency that might not be acceptable for small-scale and fast-varying networks [30]. For this reason, and for the sake of generality, we adopt a general model where RRHs can be either completely turned off or put in a sleep state [30]. Accordingly, the power consumption at time slot t for RRH $j \in \mathcal{H}$ can be expressed as follows:

$$\mathcal{C}_j^H(\mathbf{p}(t), \mathbf{y}(t)) = \mathcal{C}_j^{TX}(\mathbf{p}(t)) + \omega_R \mathcal{C}_j^A(\mathbf{y}(t)) \quad (7)$$

where ω_R is a non-negative parameter to weigh the two contributions in (7), and

$$\mathcal{C}_j^{TX}(\mathbf{p}(t)) = y_j(t) \sum_{r \in \mathcal{R}} \sum_{s \in \mathcal{S}} p_{rjs}(t) \quad (8)$$

$$\mathcal{C}_j^A(\mathbf{y}(t)) = y_j(t) \left(P_j^{(ON)} + P_j^{(F)} \right) + (1 - y_j(t)) P_j^{(sleep)} \quad (9)$$

where $P_j^{(sleep)}$ is the power consumption of the RRH j when it is put in a *sleep* state [31], [32]. It is worth mentioning that such an approach is general and also allows us to account for a broader range of applications [30]. From (7), the total power consumption for all RRHs at time slot t can be written as

$$\mathcal{C}^H(\mathbf{p}(t), \mathbf{y}(t)) = \sum_{j \in \mathcal{H}} \mathcal{C}_j^H(\mathbf{p}(t), \mathbf{y}(t)). \quad (10)$$

- *BBU Allocation*: for each scheduled mobile user, a VM has to be instantiated in the BBU pool. Also, to provide the desired SINR level to each request r , m_r computational resources must be assigned to a VM. Accordingly, the power consumption to process request r at the BBU pool can be expressed as follows:

$$\mathcal{C}_r^B(\mathbf{a}(t)) = P^{(\text{BBU})} \sum_{s \in \mathcal{S}} a_{r,s}(t) m_r \quad (11)$$

where $P^{(\text{BBU})}$ is the per resource power consumption. Thus, the overall power consumption at the BBU pool side at time slot t is $\mathcal{C}^B(\mathbf{a}(t)) = \sum_{r \in \mathcal{R}} \mathcal{C}_r^B(\mathbf{a}(t))$.

Accordingly, we have that the total weighted power consumption $\mathcal{C}(\mathbf{a}(t), \mathbf{p}(t), \mathbf{y}(t))$ in the network at time slot t is defined as follows:

$$\begin{aligned} \mathcal{C}(\mathbf{a}(t), \mathbf{p}(t), \mathbf{y}(t)) &= \mathcal{C}^{\mathcal{TX}}(\mathbf{p}(t)) + \omega_R \mathcal{C}^A(\mathbf{y}(t)) \\ &\quad + \omega_B \mathcal{C}^B(\mathbf{a}(t)) \end{aligned} \quad (12)$$

where ω_B is a non-negative parameter used to weigh the power consumption at both the RRH and BBU sides. Accordingly, the total weighted power consumption of the C-RAN system within the considered time window \mathcal{T} is

$$\mathcal{C}(\mathbf{a}, \mathbf{p}, \mathbf{y}) = \sum_{t \in \mathcal{T}} \mathcal{C}(\mathbf{a}(t), \mathbf{p}(t), \mathbf{y}(t)). \quad (13)$$

Remark 1: The above analysis clearly shows that the power consumptions at both RRH and BBU sides are tightly coupled. In fact, wireless transmissions in C-RAN systems not only require the allocation of a given amount of transmission power on each RRH, but they also rely on the instantiation of VMs and the allocation of computational resources in the BBU pool. It follows that efficient power management in C-RAN systems requires jointly reducing the power consumption of all network elements in the cloud and the Radio Access Network (RAN). We would also like to point out that the complexity and importance of such a power minimization problem is further exacerbated in the considered finite-horizon scenario, where optimal request scheduling is essential to guarantee low power consumption in the network. This motivates our work, whose objective is to design optimal resource allocation mechanisms that effectively minimize the power consumption of a C-RAN system over a finite-horizon while satisfying both SINR and scheduling constraints.

IV. PROBLEM FORMULATION

The problem of finding an optimal allocation of network resources at both the RRH and BBU sides that minimizes the weighted power consumption $\mathcal{C}(\mathbf{a}, \mathbf{p}, \mathbf{y})$ while satisfying user requirements and system constraints, can be formulated as Problem (A).

$$(\mathbf{A}) : \min_{\mathbf{a}, \mathbf{p}, \mathbf{y}} \mathcal{C}(\mathbf{a}, \mathbf{p}, \mathbf{y})$$

s.t. Constraints in (3), (4), (5), (6)

$$a_{r,s}(t) \in \{0, 1\}, \quad \forall r \in \mathcal{R}, \forall s \in \mathcal{S}, t \in [t_r^0, t_r^0 + \delta_r] \quad (14)$$

$$y_j(t) \in \{0, 1\}, \quad \forall j \in \mathcal{H}, \forall t \in \mathcal{T} \quad (15)$$

$$\sum_{t \notin [t_r^0, t_r^0 + \delta_r]} \sum_{s \in \mathcal{S}} a_{r,s}(t) = 0, \quad \forall r \in \mathcal{R} \quad (16)$$

$$\sum_{t \notin [t_r^0, t_r^0 + \delta_r]} \sum_{s \in \mathcal{S}} \sum_{j \in \mathcal{H}} p_{r,j,s}(t) = 0, \quad \forall r \in \mathcal{R} \quad (17)$$

where $\mathbf{a} = (\mathbf{a}(1), \mathbf{a}(2), \dots, \mathbf{a}(T)); \mathbf{y} = (\mathbf{y}(1), \mathbf{y}(2), \dots, \mathbf{y}(T));$ and $\mathbf{p} = (\mathbf{p}(1), \mathbf{p}(2), \dots, \mathbf{p}(T))$.

The power constraint is enforced by Constraint (3). Constraint (4) ensures that each request is accommodated exactly once, and each user is scheduled to only one of the available subcarriers. The SINR constraint is defined by the non-linear Constraint (5), and Constraint (6) prevents the system from allocating more computational resources than those available in the BBU pool. Finally, Constraints (14), (15), (16) and (17) guarantee the feasibility of the solution.

V. OPTIMAL OFFLINE SOLUTION

Problem (A) aims at reducing the weighted power consumption of the system while jointly: i) allocating requests to the available sub-carriers, iix) activating VMs in the BBU pool and assigning computational resources according to (1), iii) selecting the subset of active RRHs, and iv) controlling their transmission power to satisfy QoS requirements. In more detail, Problem (A) is formulated as an MINLP which is well-known to be NP-hard.

Specifically, Problem (A) is combinatorial, and an exhaustive search approach would result in exponential time solutions whose application to realistic scenarios is unfeasible. To overcome the above issues, and to reduce the complexity of the optimal solution, we propose the exploitation of Dynamic Programming (DP) techniques. In the remainder of this paper, we assume that a feasible solution to Problem (A) exists. However, the existence of a solution can be verified by executing a feasibility test.

In the language of DP, we define:

- *System state*: at each time slot t , the state of the system is defined as the set $\mathcal{R}(t)$ of active requests that have not yet been accommodated. Specifically, we have that $\mathcal{R}(t) = \{r \in \mathcal{R} : t \in [t_r^0, t_r^0 + \delta_r], \sum_{\tau=1}^{t-1} \sum_{s \in \mathcal{S}} a_{r,s}(\tau) = 0\}$;
- *Action*: at each time slot t , we need to find the optimal scheduling policy $\mathbf{a}(t)$, the subset $\mathbf{y}(t)$ of active RRHs to serve those requests, and the transmission power profile $\mathbf{p}(t)$. Accordingly, the actions to be taken can be defined as the 3-tuple $(\mathbf{a}(t), \mathbf{y}(t), \mathbf{p}(t))$;
- *Single slot reward*: the single slot reward consists in the single slot weighted power consumption $\mathcal{C}(\mathbf{a}(t), \mathbf{p}(t), \mathbf{y}(t))$ in (12).

Accordingly, to solve the problem through DP, for each time slot $t \in \mathcal{T}$, we write the Bellman's equation [33] as

$$\begin{aligned} J(\mathcal{R}(t), t) &= \min_{\mathbf{a}(t), \mathbf{y}(t)} \Psi(\mathbf{a}(t), \mathbf{y}(t)) + \omega_R \mathcal{C}^A(\mathbf{y}(t)) \\ &\quad + \omega_B \mathcal{C}^B(\mathbf{a}(t)) + J(\mathcal{R}(t+1), t+1) \end{aligned}$$

$$\begin{aligned}
\text{s.t. } & \sum_{\tau=t}^T \sum_{s \in \mathcal{S}} a_{rs}(\tau) = 1, \quad \forall r \in \mathcal{R}(t) \\
& \sum_{r \in \mathcal{R}(t)} \sum_{s \in \mathcal{S}} m_r a_{rs}(t) \leq M \\
& a_{rs}(t) \in \{0, 1\}, \quad \forall r \in \mathcal{R}(t), \forall s \in \mathcal{S} \\
& y_j(t) \in \{0, 1\}, \quad \forall j \in \mathcal{H} \\
& \sum_{s \in \mathcal{S}} a_{rs}(t) = 0, \quad \forall r \notin \mathcal{R}(t)
\end{aligned} \tag{18}$$

where $J(\mathcal{R}(T+1), T+1) = 0$ for all $\mathcal{R}(T+1)$, and

$$\begin{aligned}
& \Psi(\mathbf{a}(t), \mathbf{y}(t)) \\
& = \min_{\mathbf{p}(t)} \sum_{r \in \mathcal{R}^*(\mathbf{a}(t))} \sum_{s \in \mathcal{S}_r^*(\mathbf{a}(t))} \sum_{j \in \mathcal{H}^*(\mathbf{y}(t))} p_{rjs}(t) \\
\text{s.t. } & \sum_{r \in \mathcal{R}^*(\mathbf{a}(t))} \sum_{s \in \mathcal{S}_r^*(\mathbf{a}(t))} p_{rjs}(t) \leq P_j, \quad \forall j \in \mathcal{H}^*(\mathbf{y}(t)) \\
& \text{SINR}_{r,s}(t) \geq \gamma_r, \quad \forall s \in \mathcal{S}_r^*(\mathbf{a}(t)), \forall r \in \mathcal{R}^*(\mathbf{a}(t)) \\
& p_{rjs}(t) = 0, \quad \forall r \notin \mathcal{R}^*(\mathbf{a}(t)) \\
& p_{rjs}(t) = 0, \quad \forall j \notin \mathcal{H}^*(\mathbf{y}(t)) \\
& p_{rjs}(t) = 0, \quad \forall r \in \mathcal{R}^*(\mathbf{a}(t)), s \notin \mathcal{S}_r^*(\mathbf{a}(t))
\end{aligned} \tag{19}$$

where, for any given tuple $(\mathbf{a}(t), \mathbf{y}(t))$, $\mathcal{R}^*(\mathbf{a}(t)) = \{r \in \mathcal{R}(t) : \sum_{s \in \mathcal{S}} a_{rs} = 1\}$, $\mathcal{S}_r^*(\mathbf{a}(t)) = \{s \in \mathcal{S} : a_{rs} = 1, r \in \mathcal{R}^*(\mathbf{a}(t))\}$, and $\mathcal{H}^*(\mathbf{y}(t)) = \{j \in \mathcal{H} : y_j(t) = 1\}$.

From (2), we have that the SINR constraint in problem $\Psi(\mathbf{a}(t), \mathbf{y}(t))$ is non-linear. However, the same constraint can be expressed through the equivalent linear inequality

$$\begin{aligned}
& \sum_{j \in \mathcal{H}^*(\mathbf{y}(t))} p_{rjs}(t) g_{rjs} \\
& - \gamma_r a_{rs}(t) \left(\sigma^2 + \sum_{j \in \mathcal{H}^*(\mathbf{y}(t))} \sum_{\substack{r' \in \mathcal{R}^*(\mathbf{a}(t)) \\ r' \neq r}} p_{r'js}(t) g_{r'js} \right) \geq 0
\end{aligned} \tag{20}$$

Since the problem $\Psi(\mathbf{a}(t), \mathbf{y}(t))$ is a minimization one, it is straightforward to show that the SINR constraint is an active constraint, i.e., the optimal solution of the problem $\Psi(\mathbf{a}(t), \mathbf{y}(t))$ implies that the SINR constraint in (20) must be met with equality. Accordingly, the problem $\Psi(\mathbf{a}(t), \mathbf{y}(t))$ can be restated as a Linear Programming (LP) one. Specifically, it can be easily shown that the objective function and all constraints in $\Psi(\mathbf{a}(t), \mathbf{y}(t))$ are convex functions. Therefore, the LP problem is also convex, and any feasible local minimum solution is also a global solution to the problem. For any given tuple $(\mathbf{a}(t), \mathbf{y}(t))$ and time slot t , we solve the single-stage power control problem $\Psi(\mathbf{a}(t), \mathbf{y}(t))$ by using standard interior-point or simplex methods.

By exploiting DP, it is possible to obtain the optimal solution to the weighted power consumption minimization problem. Specifically, at each stage, we consider all possible combina-

tions of the outstanding request set $\mathcal{R}(t)$. Then, we consider all possible combinations of $(\mathbf{a}(t), \mathbf{y}(t))$. For any given combination $(\mathbf{a}(t), \mathbf{y}(t))$, we solve the power allocation problem $\Psi(\mathbf{a}(t), \mathbf{y}(t))$ which is LP and can be solved with polynomial complexity. Instead, the single slot optimization problem in (18) is an Integer Linear Programming (ILP) problem which can be solved through the branch and bound approaches whose worst-case computational complexity equals that of exhaustive search algorithms. Finally, we exploit backward induction [33] to solve the Bellman's equation and find the optimal solution of the problem.

Let R be the maximum number of requests in the system. The number of combinations of the outstanding request set is 2^R . The number of combinations of $\mathbf{y}(t)$ and $\mathbf{a}(t)$ are 2^H and $(S+1)^R$, respectively. Thus, the single slot optimization problem in the Bellman's equation has complexity $\mathcal{O}(2^{R+H}(S+1)^R)$. Let O_P be the complexity of the power control problem. The overall complexity of the finite-horizon power consumption minimization problem over T slots is $\mathcal{O}(TO_P(S+1)^R 2^{R+H})$. That is, finding the optimal solution of the considered problem results in exponential computational complexity.

VI. ONLINE GREEDY ALGORITHM

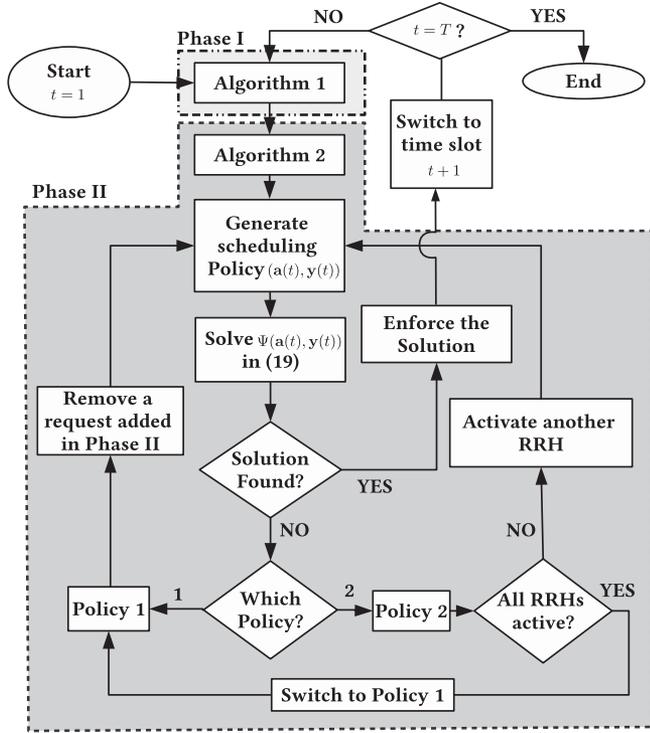
The offline solution in Section V is designed to obtain an optimal solution of Problem (A). However, it does not scale well with the number of variables in the problem and requires a priori knowledge of all the requests submitted by all network users. Accordingly, to obtain an optimal solution in large-scale and dense networks within a reasonable amount of time is unrealistic. Also, requests submitted by network users are expected to arrive in real-time and are not available in advance. Therefore, alternative online approaches must be considered.

At any given time instant t , $\mathcal{R}(t)$ is the set of outstanding requests. For the sake of readability, in the following, we omit the time slot index t . It is worth noting that network nodes dynamically submit a request and no information concerning their arrival time and minimum SINR requirements is available. In such an uncertain scenario, optimality should be relaxed, and a sub-optimal solution needs to be considered. For these reasons, in this section, we propose a sub-optimal online algorithm which can be implemented with polynomial time complexity.

As shown in Fig. 2, the proposed greedy algorithm comprises two phases. Phase I is devoted to the computation of a greedy orthogonal scheduling policy that accounts for deadline constraints and limits to zero (or to a small constant factor) interference among users. Phase II is devoted to the exploitation of JT and spectrum sharing to schedule additional requests while satisfying users' requirements. The technical details of Phase I and Phase II are described in Subsection VI-A and VI-B, respectively.

A. Phase I: Greedy Orthogonal Scheduling

Let $\mathcal{H}^\epsilon = \emptyset$, and $\mathcal{H}_\epsilon^\perp = \mathcal{H}$, where ϵ is a parameter whose importance *w.r.t.* the proposed greedy algorithm will be described in Step I.4 in this subsection. For each $r \in \mathcal{R}$, $j \in \mathcal{H}$ and $s \in \mathcal{S}$,

Fig. 2. Block diagram of the proposed greedy algorithm when $\epsilon = 0$.

we define the following parameters

$$q_r = \max\{0, t - t_r^0\} \quad (21)$$

$$\xi_{rjs} = \frac{\gamma_r \sigma^2}{g_{rjs}}. \quad (22)$$

At each time slot t , q_r is the *waiting time* (or queueing time) of request $r \in \mathcal{R}$. That is, q_r indicates the number of time slots that request r spent inside the BBU pool queue without being scheduled. ξ_{rjs} represents the minimum amount of power to fulfill the minimum average SINR level requirement of request r on channel s when served by RRH j without any other interfering transmission. Intuitively, smaller values of γ_r , i.e., loose SINR requirements, and high channel gain coefficients g_{rjs} , i.e., better channel conditions, lead to lower transmission power requirements ξ_{rjs} . Conversely, poor channel quality and high SINR requirements lead to larger values of ξ_{rjs} .

The algorithmic procedure of Phase I is summarized in Algorithm 1 and it is described in the following.

- *Step I.1:* For each $j \in \mathcal{H}$, we define $\xi_j = \{\xi_{rjs} : \xi_{rjs} \leq P_j, r \in \mathcal{R}, s \in \mathcal{S}\}$. We also generate $\nu_j = (\nu_{rjs})_{r \in \mathcal{R}, s \in \mathcal{S}}$ with

$$\nu_{rjs} = \frac{q_r + 1}{\xi_{rjs}} \quad (23)$$

Intuitively, (23) has high values when the request r : i) requires a small amount of transmission power to meet the SINR constraint; and ii) already spent several time slots in the system without being scheduled. In this step, we sort ν_j in ascending order. The obtained ordering is then

used to sort ξ_j .¹ This approach generates an ordering of ξ_j where requests that are approaching their deadline are prioritized. Conversely, the scheduling of requests that are still far away from their deadline is delayed in time. This strategy is known in the literature as Earliest Deadline First (EDF) [34], and it has been successfully utilized many times to design efficient greedy algorithms [35], [36]. The rationale behind (23) is twofold, as priority is given to those requests that i) are approaching their deadline and ii) require the least amount of power to satisfy their minimum SINR requirement. Recall that any unscheduled request makes the Constraint (4) unsatisfied, and thus generates an unfeasible solution to Problem (A). Also, requests associated to low values of ξ_{rjs} are the ones that require lower transmission power to satisfy their minimum SINR requirement. Accordingly, the ordering generated through (23) jointly aims at minimizing the objective function of Problem (A) and enforcing Constraint (4).

- *Step I.2:* For each $j \in \mathcal{H}$, we build a greedy scheduling policy $\xi_j^S \subseteq \xi_j$ as follows. We consider only those requests which require the lowest transmission power to be satisfied, while guaranteeing that P_j bounds the overall transmission power. That is, we schedule those requests in \mathcal{R} with the smallest ξ_{rjs} in ξ_j , such that $\sum_{\xi \in \xi_j^S} \xi \leq P_j$. We assume that each RRH can assign a channel to no more than one request at a time. Furthermore, from (4), we have that each request can be scheduled on no more than one channel. Therefore, from the orthogonality assumption, in ξ_j^S there could not be two requests sharing the same channel, and each request can appear only once.
- *Step I.3:* We pick the RRH which schedules the highest number of requests with the lowest power consumption. That is, we select $j^* \in \mathcal{H}$ such that $j^* = \arg \max_{j \in \mathcal{H}} \{|\xi_j^S|\}$. Ties are broken by selecting the RRH such that the overall power consumption is minimum, i.e., $j^* = \arg \min_{j \in \mathcal{H}} \{\sum_{\xi \in \xi_j^S} \xi + P_j^{(\text{ON})} + P_j^{(\text{F})}\}$. We add j^* to $\mathcal{H}^{(I)}$, i.e., $\mathcal{H}^{(I)} = \mathcal{H}^{(I)} \cup \{j^*\}$.
- *Step I.4:* Let j^* be the RRH selected at Step I.3. We build a candidate greedy scheduling policy ϕ_{j^*} such that $\phi_{j^*} = \{(r, s) \in \mathcal{R} \times \mathcal{S} : \xi_{rj^*s} \in \xi_{j^*}^S\}$. Then, we consider

$$\mathcal{H}_\epsilon^\perp(\phi_{j^*}) = \{j \in \mathcal{H} \setminus \mathcal{H}^{(I)} : g_{rjs} \leq \epsilon, \forall (r, s) \in \phi_{j^*}\} \quad (24)$$

which we define as the ϵ -orthogonal set of RRHs whose interference to the scheduling in ϕ_{j^*} is upper-bounded² by a small multiple factor of ϵ . Intuitively, if $\epsilon = 0$, it means that transmissions performed by RRHs in $\mathcal{H}_0^\perp(\phi_{j^*})$ do not interfere with the scheduling ϕ_{j^*} . Instead, small positive ϵ results in small tolerable interference values.

- *Step I.5:* Requests already in ϕ_{j^*} are removed from \mathcal{R} , i.e., $\mathcal{R} = \mathcal{R} \setminus \{r \in \mathcal{R} : \exists \xi_{rj^*s} \in \xi_{j^*}^S\}$. Also, the set $\mathcal{H}_\epsilon^\perp$ of

¹Note that this step is not the same as simply ordering ξ_j in ascending order as the two resulting orderings are generally different.

²Recall that when r is served by RRH j on channel s , the interference at r is $i_{rks} = g_{rks}p$, where p represents the transmission power of an interfering RRH $k \in \mathcal{H} \setminus \{j\}$ on channel s . In this case, $g_{rks} = i_{rks}/p$. Thus, we can effectively limit the experienced interference at r by a factor proportional to $\epsilon \geq 0$ by allowing transmissions from any RRH k such that $g_{rks} \leq \epsilon$.

Algorithm 1: Phase I: Greedy Orthogonal Scheduling.

```

1:  $\mathcal{H}^{(I)} \leftarrow \emptyset$ ;
2:  $\mathcal{H}_\epsilon^\perp \leftarrow \mathcal{H}$ ;
3: while  $(\mathcal{H}_\epsilon^\perp \neq \emptyset) \vee (\mathcal{R} \neq \emptyset) \vee (\sum_{j \in \mathcal{H}^{(I)}} \sum_{z \in \phi_j} m_z$ 
  +  $\min_{r \in \mathcal{R}} m_r > M)$  do
4:   for each  $j \in \mathcal{H}$  do
5:      $\xi_j \leftarrow \{\xi_{rjs} : \xi_{rjs} \leq P_j, r \in \mathcal{R}, s \in \mathcal{S}\}$ ;
6:     Sort  $\nu_j$  in ascending order;
7:     Sort  $\xi_j$  with respect to  $\nu_j$ ;
8:     Compute  $\xi_j^S \subseteq \xi_j$  as in Step I.2;
9:   end for
10:   $j^* \leftarrow \arg \max_{j \in \mathcal{H}_\epsilon^\perp} \{|\xi_j^S|\}$ 
11:   $\mathcal{H}^{(I)} \leftarrow \mathcal{H}^{(I)} \cup \{j^*\}$ 
12:   $\phi_{j^*} \leftarrow \{(r, s) \in \mathcal{R} \times \mathcal{S} : \xi_{rj^*s} \in \xi_{j^*}^S\}$ ;
13:   $\mathcal{H}_\epsilon^\perp(\phi_{j^*}) \leftarrow \{j \in \mathcal{H} \setminus \mathcal{H}^{(I)} : g_{rjs} \leq \epsilon, \forall (r, s) \in \phi_{j^*}\}$ ;
14:   $\mathcal{R} \leftarrow \mathcal{R} \setminus \{r \in \mathcal{R} : \exists \xi_{rj^*s} \in \xi_{j^*}^S\}$ ;
15:   $\mathcal{H}_\epsilon^\perp \leftarrow \mathcal{H}_\epsilon^\perp(\phi_{j^*}) \cap \mathcal{H}_\epsilon^\perp$ ;
16:   $\phi^{(I)}(j^*) \leftarrow \phi_{j^*}$ ;
17: end while
18: return  $\mathcal{H}^{(I)}, \phi^{(I)} = (\phi^{(I)}(j))_{j \in \mathcal{H}^{(I)}}$ ;

```

orthogonal RRHs is updated such that $\mathcal{H}_\epsilon^\perp = \mathcal{H}_\epsilon^\perp(\phi_{j^*}) \cap \mathcal{H}_\epsilon^\perp$. Then, Step I.2 is iteratively re-executed among the remaining RRHs in $\mathcal{H}_\epsilon^\perp$, and the best RRH in $\mathcal{H}_\epsilon^\perp$ is selected again until $\mathcal{H}_\epsilon^\perp = \emptyset$ or no more requests can be scheduled as there are no more computational resources in the BBU pool. That is, $\sum_{j \in \mathcal{H}^{(I)}} \sum_{z \in \phi_j} m_z + \min_{r \in \mathcal{R}} m_r > M$.

B. Phase II: JT and Channel Sharing Scheduling

For each RRH $j \in \mathcal{H}^{(I)}$, let $\phi^{(I)}(j)$ be the scheduling policy at the end of Phase I. Accordingly, for each RRH $j \in \mathcal{H}^{(I)}$ we calculate its residual power \tilde{p}_j under policy $\phi^{(I)}(j)$ as follows:

$$\tilde{p}_j = P_j - \sum_{s \in \mathcal{S}} \sum_{r \in \phi^{(I)}(j)} \xi_{rjs} \quad (25)$$

and we define $\mathcal{H}^{(II)}$ as

$$\mathcal{H}^{(II)} = \{j \in \mathcal{H}^{(I)} : \tilde{p}_j > 0\} \quad (26)$$

Intuitively, $\mathcal{H}^{(II)}$ is the subset of activated RRHs whose residual power is positive at the beginning of Phase II. Such residual power can be used to schedule multiple user transmissions on the same channel on the same RRH, or to perform JT operations through multiple RRHs that transmit to the same user. To this end, in the following we first derive a scheduling policy $\phi^{(II)}(j)$. At the beginning of Phase II, $\phi^{(II)}(j)$ is empty, of course. Then, we use $\phi^{(II)}(j)$ to derive a joint user scheduling and power allocation strategy $(\mathbf{a}(t), \mathbf{p}(t), \mathbf{y}(t))$.

The computation of $\phi^{(II)}$ is described in the following. For the sake of clarity, the same procedures are also illustrated in Algorithm 2.

- *Step II.1:* We select the request $r^* \in \mathcal{R}$ which corresponds to the minimum required transmission power and can be scheduled by exploiting the residual power of the RRHs in

Algorithm 2: Computation of $\phi^{(II)}$.

```

1: for each  $j \in \mathcal{H}^{(I)}$  do
2:    $\tilde{p}_j \leftarrow P_j - \sum_{s \in \mathcal{S}} \sum_{r \in \phi^{(I)}(j)} \xi_{rjs}$ ;
3: end for
4:  $\mathcal{H}^{(II)} \leftarrow \{j \in \mathcal{H}^{(I)} : \tilde{p}_j > 0\}$ 
5: while  $(\mathcal{H}^{(II)} \neq \emptyset) \vee (\mathcal{R} \neq \emptyset) \vee (\sum_{l \in \mathcal{H}^{(I)}} \sum_{z \in \phi^{(I)}(l)} m_z$ 
  +  $\sum_{l \in \mathcal{H}^{(II)}} \sum_{z \in \phi^{(II)}(l)} m_z + \min_{r \in \mathcal{R}} m_r > M)$  do
6:   Compute  $(r^*, j^*, s^*)$  as in Step II.1;
7:    $\phi^{(II)}(j^*) \leftarrow \phi^{(II)}(j^*) \cup \{(r^*, s^*)\}$ ;
8:    $\mathcal{R} \leftarrow \mathcal{R} \setminus \{r^*\}$ ;
9:    $\tilde{p}_{j^*} \leftarrow \tilde{p}_{j^*} - \xi_{r^*j^*s^*}$ ;
10:  if  $\tilde{p}_{j^*} \leq 0$  then
11:     $\mathcal{H}^{(II)} \leftarrow \mathcal{H}^{(II)} \setminus \{j^*\}$ ;
12:  end if
13: end while
14: return  $\phi^{(II)}$ ;

```

$\mathcal{H}^{(II)}$. Specifically, we select (r^*, j^*, s^*) such that

$$\xi_{r^*j^*s^*} = \min \left\{ \xi_{r,j,s} : \xi_{r,j,s} < \tilde{p}_j, \sum_{l \in \mathcal{H}^{(I)}} \sum_{z \in \phi^{(I)}(l)} m_z \right. \\ \left. + \sum_{l \in \mathcal{H}^{(II)}} \sum_{z \in \phi^{(II)}(l)} m_z + m_r \leq M, \right. \\ \left. r \in \mathcal{R}, j \in \mathcal{H}^{(II)}, s \in \mathcal{S} \right\}. \quad (27)$$

- *Step II.2:* We update the Phase II scheduling policy $\phi^{(II)}(j^*) = \phi^{(II)}(j^*) \cup \{(r^*, s^*)\}$.
- *Step II.3:* We remove r^* from the outstanding requests set, i.e., $\mathcal{R} = \mathcal{R} \setminus \{r^*\}$.
- *Step II.4:* We update the residual power of j^* as follows: $\tilde{p}_{j^*} = \tilde{p}_{j^*} - \xi_{r^*j^*s^*}$. If $\tilde{p}_{j^*} \leq 0$, we remove j^* from $\mathcal{H}^{(II)}$.
- *Step II.5:* Step II.1 is iteratively re-executed as soon as one of the following conditions is satisfied: i) all the residual power has been exhausted, i.e., $\mathcal{H}^{(II)} = \emptyset$; ii) the set of outstanding requests is empty, i.e., $\mathcal{R} = \emptyset$; iii) no more requests can be processed in the BBU pool, i.e., $\sum_{l \in \mathcal{H}^{(I)}} \sum_{z \in \phi^{(I)}(l)} m_z + \sum_{l \in \mathcal{H}^{(II)}} \sum_{z \in \phi^{(II)}(l)} m_z + \min_{r \in \mathcal{R}} m_r > M$ for all $r \in \mathcal{R}$.

Let $\phi = (\phi^{(I)}, \phi^{(II)})$ be the scheduling policy obtained at the end of Phase I and Phase II, where $\phi^{(I)} = (\phi^{(I)}(j))_{j \in \mathcal{H}^{(I)}}$, and $\phi^{(II)} = (\phi^{(II)}(j))_{j \in \mathcal{H}^{(II)}}$.

We set $a_{rs} = 1$ for all the scheduled requests such that $(r, s) \in \phi$, and we set $y_j = 1$ for those activated RRHs $j \in \mathcal{H}^{(II)}$. Thus, at each time slot t , we obtain the RRH activation vector $\mathbf{a}(t)$ and the request scheduling matrix $\mathbf{y}(t)$. Those two variables are used to compute $\Psi(\mathbf{a}(t), \mathbf{y}(t))$ and to solve the power minimization problem in (19). If a solution is found, the resulting scheduling and transmission policy is enforced. Otherwise, if no solution exists, two alternative approaches can be followed. Specifically, we can either i) unschedule the extra requests, or ii) activate an additional RRH to search for a feasible power control solution.

Those two approaches can be summarized in the two following policies:

- 1) *Policy 1*: We solve the power control problem (19) by iteratively removing the requests in $\phi^{(II)}$ whose required minimum transmission power ξ_{rjs} is maximum until a solution is computed. If the requests in $\phi^{(II)}$ are all removed, then the original orthogonal scheduling $\phi^{(I)}$ is found. Accordingly, if $\epsilon = 0$, a solution to the problem (19) must exist by the construction of the greedy orthogonal scheduling policy $\phi^{(I)}$. Otherwise, if $\epsilon > 0$ and a solution to (19) does not exist, then we set $\epsilon = 0$ and we re-execute Phase I, which surely admits a solution.
- 2) *Policy 2*: We iteratively launch the power control algorithm by iteratively activating the least power consuming RRH in $\mathcal{H} \setminus \mathcal{H}^{(I)}$ until we find a feasible solution. If all RRHs have been activated and no solutions are found, then we launch Policy 1 until a feasible solution is obtained.

For illustrative purposes, in Fig. 2 we present the block diagram corresponding to the proposed greedy algorithm when $\epsilon = 0$. It is worth noting that if a solution is found, the algorithm enforces the obtained scheduling policy and moves to the next time slot. The block diagram for the case where $\epsilon > 0$ is similar to that shown in Fig. 2. The only difference is that if no solutions are found at the end of Policy 2 and Policy 1, then the algorithm is re-executed by setting $\epsilon = 0$, which, at least, ensures that Phase I generates an orthogonal greedy scheduling policy.

The complexity of the ordering in Step I.1 is $\mathcal{O}(RS \log RS)$. The operation is performed H times. Therefore, Step I.1 has complexity $\mathcal{O}(HRS \log RS)$. Steps I.2 – I.5 have complexity $\mathcal{O}(HR)$. However, they are iterated over all the available RRHs until a greedy orthogonal scheduling policy is obtained. Accordingly, they have complexity $\mathcal{O}(H^2R)$, and Phase I has overall complexity $\mathcal{O}(HRS \log RS + H^2R)$. Similarly, it can be shown that Phase II has complexity $\mathcal{O}(H^2R)$. Policy 1 has complexity $\mathcal{O}(R)$, while Policy 2 has complexity $\mathcal{O}(H + 2R)$. Therefore, the overall complexity of the proposed greedy algorithm is $\mathcal{O}(HRS \log RS + H^2R)$.

VII. NUMERICAL ANALYSIS

In this section, we assess the achievable performance of the above proposed solutions through extensive numerical simulations. Specifically, in Section VII-A we analyze the performance of the optimal solution. The achievable performance of the proposed greedy scheduling algorithm is discussed in Section VII-B.

Our study not only focuses on the power consumption of the C-RAN system under the algorithms proposed in the previous Sections, but it also investigates two relevant metrics, namely *satisfied user ratio* and *RRH activation probability*. The former indicates the percentage of users whose requests are satisfied by the network. The latter gives us important information on the number of RRHs that must be effectively turned on to support user data transmissions and guarantee minimum SINR requirements.

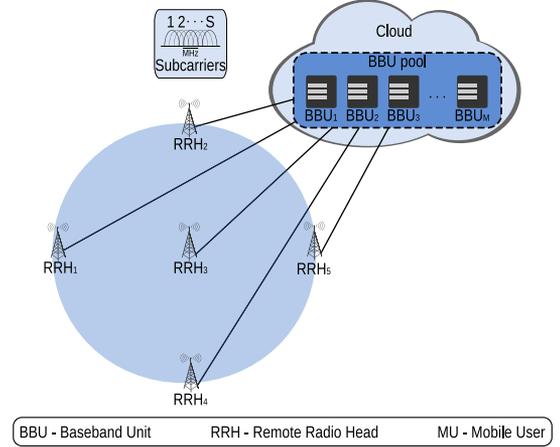


Fig. 3. The simulated C-RAN network.

To assess the performance of the proposed solutions, we consider a circular network scenario. Despite its simplicity, this model has been identified as a good candidate for performance evaluation in C-RAN systems, and has been effectively used many times in the literature [9], [37]–[41] as a benchmark for power allocation, user scheduling, and resource allocation algorithms. In our simulations, we assume that $H = 5$ RRHs and a BBU pool are deployed in a circular area as shown in Fig. 3. The corresponding fiber power costs $P_j^{(F)}$, which depend on the distance between the BBU pool and the RRHs, are $\mathbf{P}^{(F)} = \{2, 1, 1, 2, 1\}$ W. Let us point out that our solution is general and can be utilized independently of the actual distribution of users in the network. However, for simulation purposes only, we model the position of network users as a random variable with circular uniform distribution [24], [42], [43]. Specifically, at each simulation run, the position of network users is randomly generated within a circle whose radius is set to $L = 500$ m. Channel gain coefficients are generated according to the path-loss model in [44] for Rayleigh fading channels. The activation and sleep power costs are assumed to be equal for all the RRHs. Specifically, we set $P_j^{(ON)} = 130$ W [31], [45] and $P_j^{(sleep)} = 75$ W [31]. The maximum transmission power level for each RRH is set to $P_j = 48$ dBm [45]. We consider the case where the amount of computational resources to process each request increases linearly with the achievable Shannon capacity, *i.e.*, the slope in (1) is set to $\theta = 1$. Also, we assume that the amount of computational resources m_{VM} to process data requests in the BBU pool is $m_{MV} = 5$. Accordingly, we have $m_r = m$ for all $r \in \mathcal{R}$, which yields $P^{(BBU)}(m_r) = P^{(BBU)}(m_z)$ for all $r, z \in \mathcal{R}$. We assume that such a cost is $P^{(BBU)}(m_r) = 1$ W. The weight parameters are set to $\omega_R = 0.01$ and $\omega_B = 0.1$. Finally, we assume that users submit their requests according to a binomial distribution [46] with success probability $p = 0.5$, and the number of trials equal to $n = R_{\max}$, where R_{\max} represents the maximum number of users in the network. The results shown in this subsection are averaged over 5000 simulation runs.

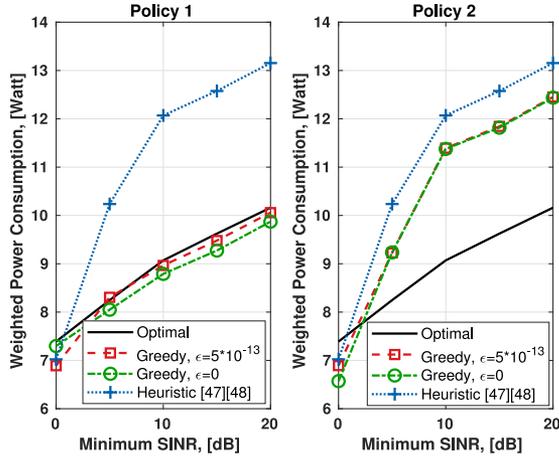


Fig. 4. Weighted power consumption \mathcal{C} as a function of the minimum average SINR requirement level for different scheduling algorithms.

A. Optimal Offline Solution

In this subsection, we assess the performance of the optimal offline solution proposed in Section V, and we compare it with other scheduling policies. As already discussed in Section V, to find an optimal solution to the joint scheduling and power allocation problem is a NP-hard problem, i.e., it has exponential complexity in the number of variables of the problem, which makes it infeasible to compute an optimal solution even for small network instances. Thus, in this section only, we restrict our performance evaluation to the case where only RRH_1 and RRH_5 can be activated, while the remaining $RRHs$ are switched off.³ Furthermore, we consider a system where $S = 2$ subcarriers are available for data transmission. The optimization horizon is set to $T = 3$, and we assume that all requests have to be accommodated before the horizon is reached. Finally, we assume that number of users in the network is $R_{\max} = 7$.

In Fig. 4, we show the weighted power consumption \mathcal{C} in (13) as a function of the minimum average SINR requirement level and the parameter ϵ in (24). Specifically, we compare the optimal offline solution (solid lines) with two other algorithms: the greedy online algorithm proposed in Section VI (dashed lines), and the heuristic approach considered in [47] and [48] where all $RRHs$ are turned on simultaneously when there is at least one request to be served (dotted lines). In general, the power consumption always increases as the minimum average SINR requirement level increases. Also, the power consumption under the optimal policy is generally lower than that achieved by all the other considered algorithms. It is worth noting that Fig. 4 shows some cases where the power consumption of the network under the greedy algorithm is lower than that achieved when the optimal solution is considered. This result is explained in Fig. 5, where we show that the above phenomenon arises in those cases where the greedy algorithm does not produce a feasible solution that satisfies the minimum SINR constraints, i.e., when some requests cannot be satisfied. By reducing the number of served

³The case where all $RRHs$ can be selected will be extensively investigated in Section VII-B.

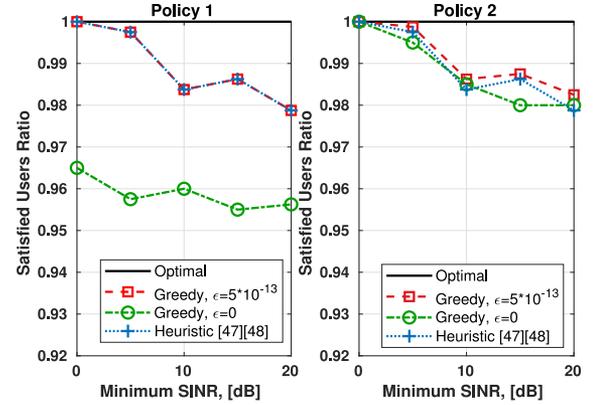


Fig. 5. Average satisfied user ratio as a function of the minimum SINR requirement level for different scheduling algorithms.

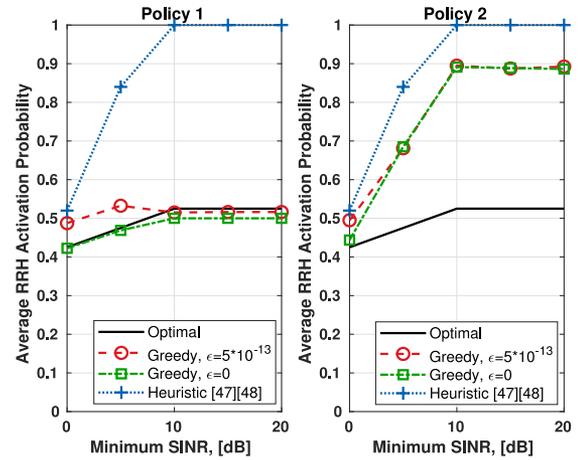


Fig. 6. Average RRH activation percentage as a function of the minimum average SINR requirement level for different scheduling algorithms.

users, the corresponding power consumption is also reduced, thus explaining why the greedy algorithm shows lower power consumption in some cases. As expected, when all requests are satisfied, i.e., the satisfied users ratio is equal to 1, the optimal algorithm always provides the best performance. It is also worth noting that Policy 1 achieves near-optimal performance if compared to the optimal solution, and the additional cost introduced by the greedy algorithm is small, and anyway lower than that introduced by the heuristic approach. Although Policy 1 slightly under-performs Policy 2 in terms of satisfied users ratio, it both achieves very high satisfaction percentage, (i.e., 96% of the total number of users) and also consumes less power than Policy 2. For network operators, the combination of the greedy algorithm and Policy 1 presents an opportunity to save energy in those scenarios where the minimum SINR requirement is low. Instead, when high SINR levels are required, the greedy algorithm with Policy 2 should be preferred.

To better understand the motivation behind the above findings, in Fig. 6 we show the average activation percentage of the two $RRHs$ for the three algorithms as a function of the minimum average SINR requirement level. It is shown that

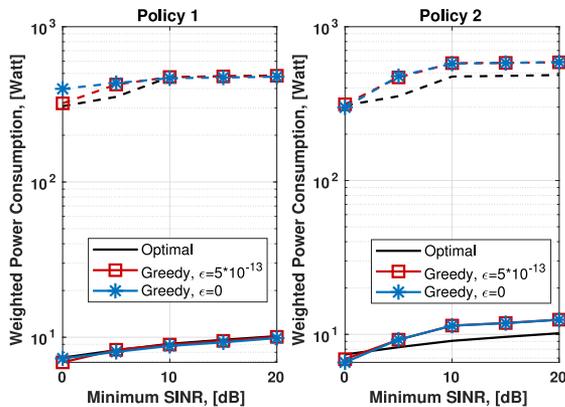


Fig. 7. Weighted power consumption \bar{C} as a function of the minimum average SINR requirement level for different weight parameter configurations (Case A: solid lines; Case B: dashed lines).

the optimal solution (solid lines) activates the lowest number of RRHs, thus resulting in low power consumption levels. On the contrary, both the proposed (dashed lines) and the heuristic (dotted lines) approaches activate a higher number of RRHs. Specifically, since the heuristic approach activates all the RRHs when at least one request has to be scheduled, it results in the highest power consumption. Instead, the activation percentage under the proposed greedy algorithm under Policy 1 is slightly higher than that achieved under the optimal policy. For C-RANs composed of RRHs with high energy activation cost, Policy 1 brings even further energy consumption benefits considering the aforementioned trade-off regarding users' satisfaction. Whereas, when Policy 2 is used, the system will benefit from near optimal user satisfaction with better energy consumption than previously proposed solutions, such as the heuristic in [47], [48].

It is worth noting that the average RRH activation probability for the heuristic approach (dotted lines) is not always equal to 1. Such a result is due to the fact that the heuristic approach activates all the RRHs if and only if there is at least one request to be scheduled. Otherwise, the RRHs remain inactive. Furthermore, the power consumption generated by the proposed greedy algorithm under both Policy 1 and Policy 2 increases as the minimum SINR level increases as well. As shown in Fig. 6, such a result is directly tied to the higher RRH activation percentage of the greedy approach when the minimum required SINR level increases. As a result, to support high-quality communications, the greedy algorithm proposed in Section VI activates additional RRHs, thus generating a higher cost if compared to the optimal solution.

Finally, in Fig. 7 and Table II we investigate the impact of the weight parameters on the overall power consumption and RRH activation probability, respectively. Specifically, in our simulations we consider the following two cases:

- *Case A*: all the power cost terms in (10) have similar amplitudes (i.e., $w_R = 0.01$ and $w_B = 0.1$). This is the case where the network operator equally weighs the power consumption of each element of the C-RAN system. Such a policy stems from the evidence that the power needed to

TABLE II
AVERAGE RRH ACTIVATION PROBABILITY FOR DIFFERENT
MINIMUM SINR REQUIREMENT

Case Name	Minimum SINR Requirement				
	0 dB	5 dB	10 dB	15 dB	20 dB
Case A	0.402	0.421	0.553	0.562	0.611
Case B	0.324	0.375	0.449	0.511	0.525

turn on one RRH (in the order of hundreds of Watts) is considerably higher if compared to the power consumption due to RF transmissions (in the order of few Watts). Accordingly, this policy tries to equally reduce the power consumption at each element of the network.

- *Case B*: the weights are set to $w_R = w_B = 1$. This case represents the one where the network operator aims at minimizing the actual power consumption of the network. In this case, more attention is given in reducing the activation of RRHs rather than reducing the transmission power of each RRH.

Intuitively, Case A generates resource allocation policies that are power conservative for each element of the network. On the contrary, Case B aims at reducing the major source of power consumption of the system while disregarding those elements whose power consumption is small.

The obtained results show that the values of the weight parameters not only impact the value of the objective function at the end of the optimization process, but they also impact the activation of RRHs. Specifically, in Case B the value of the cost term in (9) is considerably higher than the other two terms in the objective function (12). Accordingly, Table II shows that this results in a lower probability of activating all RRHs if compared to Case A, where the activation cost is weighted by $w_R = 0.01$.

B. Greedy Online Solution

As already shown in Section VI, the proposed greedy online solution has polynomial complexity. Accordingly, in this section we assume that all of the five RRHs in Fig. 3 can be activated. Furthermore, we assume that $S = 8$ subcarriers are available for data transmission, and the optimization horizon is set to $T = 10$. In Fig. 8 we show the weighted power consumption \bar{C} as a function of the minimum average SINR requirement level for different values of the orthogonality parameter ϵ and R_{\max} . Let us recall that, to accommodate users' requests, Policy 2 iteratively searches a solution by activating more RRHs. Instead, Policy 1 keeps the already activated RRHs and removes those requests which cannot be scheduled due to the limitations of the spectrum and transmission resources. Therefore, Fig. 8 shows that the power consumption when Policy 2 is enforced (dashed lines) is higher than that obtained when Policy 1 is employed (solid lines), and increases as the minimum SINR level increases. Also, as expected, as the maximum number R_{\max} of requests at each time slot increases, more RRHs have to be turned on and the power consumption increases as well. Because higher transmission power levels have to be considered

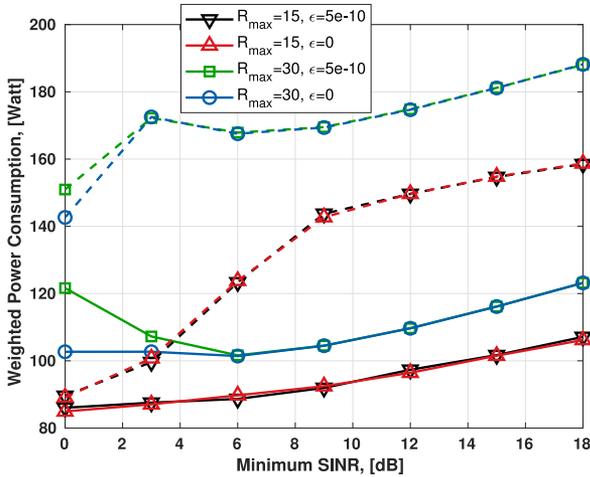


Fig. 8. Weighted power consumption C as a function of the minimum average SINR requirement level for different values of ϵ and R_{max} (Policy 1: solid lines; Policy 2: dashed lines).

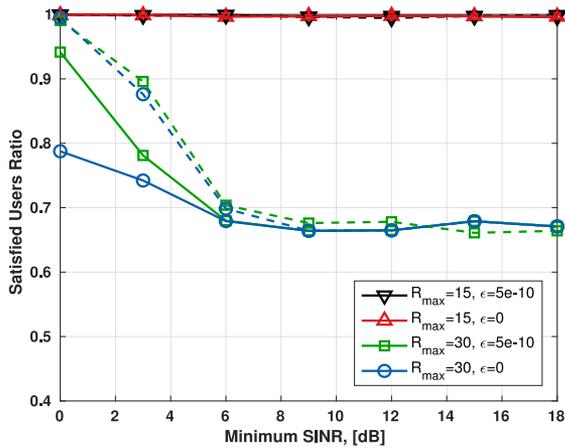


Fig. 9. Average satisfied user ratio as a function of the minimum SINR requirement level for different values of ϵ and R_{max} (Policy 1: solid lines; Policy 2: dashed lines).

and more RRHs have to be activated, introducing interference, a slightly higher power consumption is experienced when $\epsilon > 0$.

Fig. 9 shows the average proportion of satisfied users in the network as a function of the minimum average SINR requirement level for different values of ϵ and R_{max} . While Policy 1 (solid lines) is oriented towards power savings, Policy 2 (dashed lines) is user-oriented and is well-suited to satisfy a higher number of users. Specifically, Fig. 9 shows that Policy 2 performs better than Policy 1 regarding the average proportion of satisfied users. However, such a high proportion of satisfied users requires higher power consumption, as shown in Fig. 8. Also, it is shown that this proportion decreases as the minimum average SINR requirement increases. In fact, higher SINR requirements imply lower interference, which leads to a lower number of scheduled and thus satisfied users. Furthermore, by considering a positive value of ϵ , it is possible to satisfy a higher number of users when the required minimum SINR level is low. However, as already

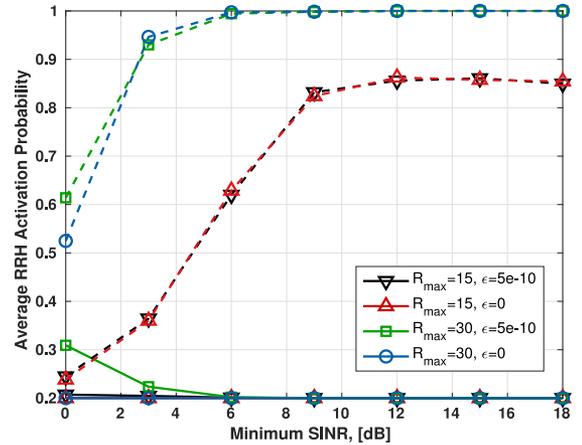


Fig. 10. Average RRH activation percentage as a function of the minimum SINR requirement level for different values of ϵ and R_{max} (Policy 1: solid lines; Policy 2: dashed lines).

shown in the above Fig. 8, this improvement comes at a cost in terms of consumed power. It is worth noting that when the number R_{max} of users in the network is small, approximately the 100% of users' requests can be satisfied. On the contrary, larger values of R_{max} generally result in a lower percentage of satisfied users. As an example, a minimum average SINR level of 10dB would make it possible to satisfy only 65% of users.

In Fig. 10, we show the average RRH activation percentage as a function of the minimum SINR requirement level for different values of ϵ and R_{max} . It is shown that the average number of activated RRHs is higher under Policy 2 (dashed lines). Instead, the average number of activated RRHs under Policy 1 (solid lines) is almost constant with respect to the minimum average SINR requirement level. Furthermore, when small values of the minimum average SINR level are considered, positive values of the parameter ϵ generate more interference in the ongoing transmissions, which pushes the network towards the activation of additional RRHs to support JT and CoMP communications. Also, while Policy 2 tries to find a feasible solution to the power allocation problem by activating additional RRHs, Policy 1 removes users' requests from the scheduling policy. Thus, Policy 2 provides a higher percentage of satisfied users as compared to Policy 1.

In Fig. 11 and Fig. 12, we show how the RRHs are activated according to the selected scheduling policy for two different values of R_{max} when $\epsilon = 5 \times 10^{-10}$. Specifically, in Fig. 11 we assume $R_{max} = 15$, and in Fig. 12 we consider the case where $R_{max} = 30$. For each minimum SINR requirement, we show five bars. Each bar corresponds to a given RRH in Fig. 3. Specifically, the i -th bar corresponds to RRH_i .

It is shown that, in general, Policy 2 activates more RRHs. Also, since RRH_3 is located at the center of the considered simulated area, it is the one which has the highest activation percentage in all the studied cases. Intuitively, being in the center of the scenario considered allows RRH_3 to serve more users than the other RRHs, which are located at the border. Also, due to its nearness to the BBU pool, RRH_3 requires less power

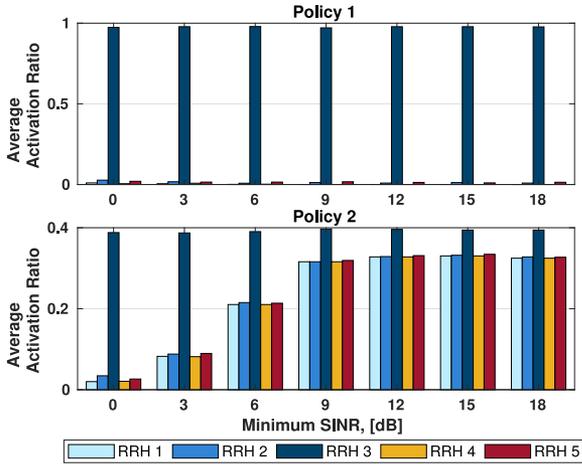


Fig. 11. Average activation ratio of each RRH as a function of the minimum average SINR requirement level for different policies when $R_{\max} = 15$.

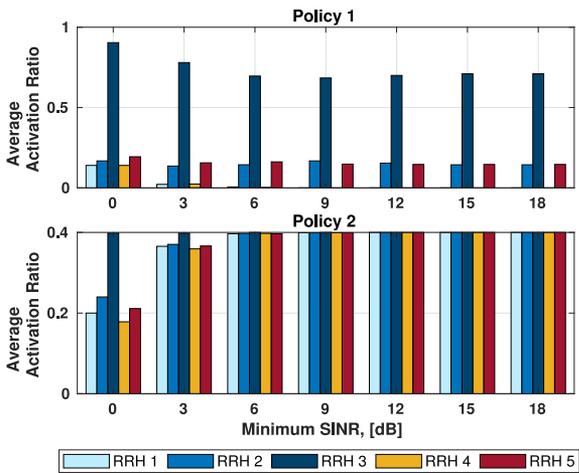


Fig. 12. Average activation ratio of each RRH as a function of the minimum average SINR requirement level for different policies when $R_{\max} = 30$.

to activate the optical fibers, e.g., $P_3^{(F)} = 1$. On the contrary, RRH₁ and RRH₄, which are far away from the BBU pool and are located at the edge of the network, have a fiber power cost of $P_1^{(F)} = P_4^{(F)} = 2$, and are the ones which show the lowest activation percentage.

It is worth noting that, due to the power constraint, each RRH can serve a limited number of requests. Thus, when the maximum number of users R_{\max} in the network is large, it is expected that all the available RRHs have to be turned on. This intuition is validated by Fig. 12, which shows that, when $R_{\max} = 30$ and Policy 2 is enforced, all the RRHs are activated with probability higher than 95%.

In Fig. 13, we analyze the power consumption of each element of the C-RAN system as a function of the minimum average SINR requirement level for different values of ϵ and R_{\max} . With respect to the RAN portion of the system, it is shown that the power consumption due to RF transmissions increases as the minimum average SINR requirement level and

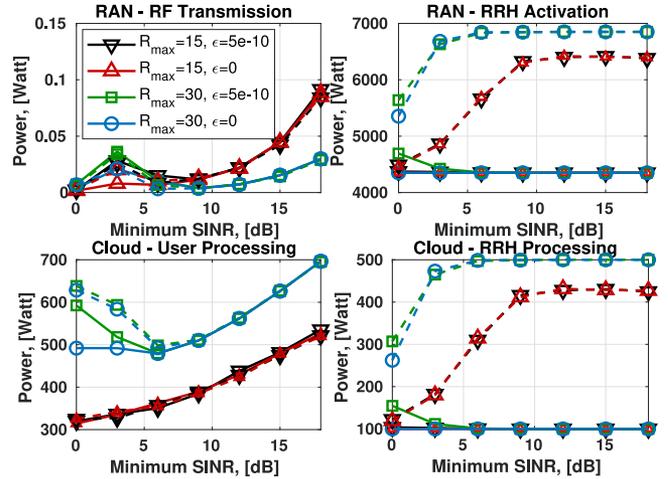


Fig. 13. Average power consumption for each element of the C-RAN system as a function of the minimum average SINR requirement level for different values of ϵ and R_{\max} (Policy 1: solid lines; Policy 2: dashed lines).

number of users increase. This results stems from the fact that to achieve higher SINR values, RRHs are required to transmit at high power. Fig. 13 also shows that the power consumption due to the activation of RRHs has similar behavior in both the cloud and RAN portions of the system. Specifically, it is interesting to note that the power consumption due to RRH activation and processing mimics the RRH activation probability illustrated in Fig. 10. Finally, in Fig. 13 we investigate the impact of user scheduling on the power consumption of the cloud portion of the C-RAN system. Results show that the higher the minimum average SINR required level, the higher the power consumption due to processing of users' data in the BBU pool. Intuitively, from (1), high QoS requirements require a large amount of computational resources in the BBU pool, which eventually results in more consumed power. Moreover, it is shown that the choice of policy does not considerably impact the power consumption due to data processing in the cloud. Instead, the power consumption significantly increases when R_{\max} is high. Specifically, the power consumption for data processing in the BBU pool when $R_{\max} = 30$ is approximately 1.25 times higher than that achieved when $R_{\max} = 15$. Although it is out of our scope, it is also worth mentioning that the decision of which policy to be used in a centralized pool may differ completely of the one taken when considering a distributed pool within a C-RAN. When distributed BBU pools are considered, RRHs are dynamically assigned to each pool, and the activation cost depends on the distance between each RRH and the corresponding associated BBU pool in a given assignment slot. In this case, the benefits and gains explained here might not hold anymore.

VIII. CONCLUSION

In this paper, we have addressed the power consumption minimization problem to schedule user requests within a finite horizon for a C-RAN. We have formulated the power consumption minimization problem as a weighted joint power allocation and

user scheduling problem accounting for both temporal and minimum SINR constraints. Also, we have formalized the problem as an MINLP, which enabled us to find an optimal offline solution based on DP techniques. Due to the computational complexity to compute the optimal solution being exponential, we have designed a heuristic greedy online algorithm of polynomial computational complexity to solve the problem in a more realistic time for C-RANs. We have then compared the outcomes of the optimal and the greedy algorithms. Our results clearly indicate that the greedy algorithm, while not optimal, achieves a good trade-off between the minimization of the power consumption and the maximization of the percentage of satisfied users. Our proposed algorithm results in power consumption that is only marginally higher than the optimum, at significantly lower complexity. We have also assessed the average activation probability, which shows a slightly increase when comparing the greedy algorithm against the optimal one.

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ferences and congresses.



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