Throughput Maximization in Cloud-Radio Access Networks using Rate-Aware Network Coding

Mohammed S. Al-Abiad, Ahmed Douik, Student Member, IEEE,
Sameh Sorour, Senior Member, IEEE and Md Jahangir Hossain, Senior Member, IEEE

Abstract—One of the most promising techniques for network-wide interference management necessitates a redesign of the network architecture known as cloud radio access network (CRAN). The cloud is responsible for coordinating multiple Remote Radio Heads (RRHs) and scheduling users to their radio resources blocks (RRBs). The transmit frame of each RRH consists of several orthogonal RRBs each maintained at a certain power level (PL). While previous works considered a vanilla version in which each RRH can serve a single user, this paper proposes mixing the flows of multiple users using instantly decodable network coding (IDNC). As such, the total throughput is maximized. The joint user scheduling and power adaptation problem is solved by designing, for each RRB, a subgraph in which each vertex represents potential user-RRH associations, encoded files, transmission rates, and PLs for one specific RRB. It is shown that the original problem is equivalent to a maximum-weight clique problem over the union of all subgraphs, called herein the CRAN-IDNC graph. Extensive simulation results are provided to attest the effectiveness of the proposed solution against state of the art algorithms. In particular, the presented simulation results reveal that the method achieves substantial performance gains for all system configurations which collaborates the theoretical findings.

Index Terms—Cloud radio access networks, coordinated scheduling, instantly decodable network coding, power allocation.

I. INTRODUCTION

O

VER the last decade, the continuously increasing demand for high-speed data transfer has been generating a severe burden on the wireless networks infrastructure. Moreover, the scarcity of the radio resources raises extra challenges for the Next Generation Mobile Networks 5G to meet the expected quality of service requirements [2]. The steady move towards dense cellular architectures in 4G partially solved the problem but raised concerns regarding interference management. Cloud-radio access networks (CRANs) is one of the most promising techniques for the Next Generation Mobile Networks 5G due to their high capabilities in mitigating interference and thus providing high data rates [3]. In CRANs, a central computing unit, known as the cloud, coordinates multiple remote radio heads (RRHs) of different sizes and possible from different tiers. Due to its centralized computation, CRANs display great ability in allocating the radio resources of the different RRHs resulting in efficient interference management.

As stated earlier, the coordinated scheduling problem is intrinsically combinatorial. Furthermore, determining the power...
levels for a pre-assigned schedule is known to be a non-convex problem. As a result, finding the optimal solution is challenging and not feasible by any polynomial-time algorithm. A large number of previous works solved the coordinated scheduling and power allocation problems separately. For example, authors of [4], [5] proposed a scheduling algorithm in heterogeneous networks assuming a preassigned association of mobile users and RRHs, e.g., proportional fair scheduling.

Recent works on CRANs, e.g., [8]–[10], suggested scheduling users to RRHs in a coordinated fashion by the cloud in order to maximize the network total ergodic capacity. The studies are extended in [6] and references therein to include the joint optimization of the scheduling with the beamforming vectors and the power level of each radio resource. Recently, for the weighted rate maximization objective function, the authors in [7] suggested a graph theory technique to solve the joint optimization optimally.

All studies mentioned above view the network solely from the physical layer without taking into consideration upper layer facts. Therefore, each RRB serves a single user in each transmission instance. However, it has been observed that users tend to have a common interest in downloading popular files, especially videos, within a small interval of time, thus creating a pool of side information in the network. To the best of the authors’ knowledge, maximizing the system throughput in a CRAN by using IDNC to allow files of different users to be scheduled simultaneously is innovative.

Different studies on IDNC revealed various code construction schemes with significant potential in minimizing multiple system parameters for different applications and network settings. For example, while the authors in [15] suggest reducing the total transmission time, i.e., the completion time, authors of [18] optimize the decoding delay. Similarly, the authors in [16] introduce a delay-based framework to reduce the completion time.

The use of IDNC in a CRAN setting brings a new set of challenges as the aim of these two techniques can be opposite. Indeed, by multiplexing their files and scheduling multiple users to the same radio resource block, the total number of targeted users increases. However, due to the heterogeneity of the achievable capacity of each user, the transmission rate of each resource block decreases. On the other hand, targeting a single user in CRAN can maximize the transmission rate of each RRB but misses the coding opportunities which could achieve further throughput and efficiency gains. Recently, IDNC had been employed in [17] in the context of a heterogeneous network setting to minimize the completion time of the users by jointly selecting the file combinations and transmission rates of each RRH. This paper aims to extend the study to the more practical and promising paradigm of CRAN. In particular, it investigates the cross-layer optimization in CRANs to achieve the maximum received throughput by jointly scheduling users to RRB/RRHs, and finding the optimal power levels of each RRB.

B. Contributions

In this work, we investigate the usage of an IDNC for throughput maximization in CRANs. Similar to the framework of [4]–[7], we consider a scheduling-level coordinated CRAN in which each user can be associated to one RRH but can be served by multiple RRBs belonging to that RRH’s frame. The main contributions and results of this work can be summarized as follows.

- Using a graph theoretical approach, we design a novel graph, called herein the CRAN-IDNC, which consists of multiple sub-graphs called power control subgraphs. Each subgraph represents the potential associations for a specific RRB wherein each vertex represents associations represented by a 6-tuple combination of RRH, RRB, user, file, transmission rate, and PL. Such a CRAN-IDNC graph takes the following aspects into consideration:
  - User Multiplexing: In each vertex, users are multiplexed to each RRB in each RRH based on their requests, i.e., mixing the flows of users, which is not addressed in the literature that looked at the problem from a physical-layer perspective. In this study, we consider the user multiplexing mechanism presented in [17] to deliver files to users.
  - Rate Adaptation: In order to benefit from the heterogeneity of the achievable capacity of each user, we consider the adaptive transmission rate mechanism in each vertex that represents the same RRB and the same RRH, such that each RRB selects the best transmission rate of all associated users. As such, throughput is maximized, and the QoS requirements of the end-users are maintained.
  - Optimal Power level: Power control solution is applied. Specifically, since each vertex consists of many associations that represent scheduled users to the same RRB across all RRHs, we consider power control optimization for each vertex. This allows us to suppress the effect of interference that comes from the same RRB in different RRHs, which in turn improves the overall system throughput.

- Using the designed CRAN-IDNC graph, the joint coordinated scheduling and power optimization problem is shown to be equivalent to a maximum-weight clique problem, which can be solved efficiently.

- Due to the complexity of the optimal solution, we use the decoupling approach mentioned in the literature to approximate the joint optimization problem efficiently. In particular, for a fixed power, the coordinated scheduling problem is solved using similar graph theory techniques as proposed in [1]. Afterward, for a fixed schedule, the power allocation problem is solved numerically. The process of iterating between coordinated scheduling and power allocation steps continues until convergence.

- Using extensive simulations, we demonstrate the effectiveness of the proposed solution against state of the art algorithms. In particular, the presented simulation results reveal that the method achieves substantial performance gains for all system configurations which collaborates the theoretical findings.

The remainder of this paper is organized as follows. Section II introduces the considered system model and param-
eters. The joint scheduling and power allocation problem formulation and graph design are illustrated in Section III. Section IV introduces the optimal joint solution and further designs a low-complexity heuristic. In order to further reduce the complexity, Section V presents an iterative algorithm. Finally, before concluding in Section VII, Section VI plots and discusses the simulation results.

II. SYSTEM MODEL AND PARAMETERS

A. Cloud Radio Access Network Model

This paper considers the downlink of a CRAN in which a computing unit is connected to a set of RRHs distributed in different geographic locations within a cell and connected to the cloud through low-rate backhaul links. These RRHs serve a set of mobile users in a single-hop transmission, i.e., all users are in the coverage of at least one RRH. For instance, Figure 1 shows a CRAN with 3 RRHs cooperating to serve 6 mobile users simultaneously.

The transmit frame of each RRH consists of Z orthogonal time/frequency RRBs that are denoted by a set Z and shown in Figure 2. Therefore, the total number of available RRBs in the system is $Z_{tot} = \mathcal{B} \times \mathcal{Z}$. Let $P_{b,z}$ be the power allocation level (PL) of the $z$-th RRB in the $b$-th RRH. Let $\mathbf{P} = [P_{b,z}]$ be a $\mathcal{B} \times \mathcal{Z}$ matrix containing the PLs of the considered network. From practical constraints, the power level of each RRB is bounded by $P_{b,z} \leq P_{b,z}^{\max}$. The cloud is responsible for scheduling users, synchronizing the transmission frames of all RRHs, and determining the PL of each RRB. Due to the limited capacity of the backhaul links, each user can be assigned to at most one RRH, but possibly to many RRBs within its frame.

Let $h_{b,z}^u(t)$ be the complex channel gain from the $z$-th RRB in the $b$-th RRH to the $u$-th user at the $t$-th transmission. The channel is assumed to be constant during the transmission time of a single uncoded/coded file and to change from one transmission to another. In our specific simulation set, we opted for the SUI model in which the channel information is affected by multiple factors, e.g., fading, shadowing, but the location of the user within the service area is the dominant factor. Such channel model leads to heterogeneous physical-layer rates from different RRBs/RRHs to different users. Moreover, we assume that there is no restriction on the model or the distribution of the channels. However, it uses the standard assumption that these values are perfectly estimated and available at the cloud. The ergodic capacity of the $u$-th user assigned to the $z$-th RRB in the $b$-th RRH can be expressed as:

$$R_{b,z}^u(t) = \log_2(1 + \text{SINR}_{b,z}^u(\mathbf{P})),$$

wherein $\text{SINR}_{b,z}^u(\mathbf{P})$ is the corresponding signal-to-interference plus noise-ratio experienced by the $u$-th user when it is assigned with RRB $z$ of the $b$-th RRH, and can be expressed as:

$$\text{SINR}_{b,z}^u(\mathbf{P}) = \frac{\langle P_{b,z} | h_{b,z}^u \rangle^2}{\sigma^2 + \sum_{b' \neq b} \langle P_{b',z} | h_{b',z}^u \rangle^2},$$

where $\sigma^2$ is the additive white Gaussian noise (AWGN) power.

As stated earlier, the transmit frame of each RRH consists of $Z$ orthogonal RRBs. Therefore, interference at the $z$-th RRB is seen only from the same $z$-th RRB in the other RRHs. In other words, $\text{SINR}_{b'}^u(\mathbf{P})$ depends solely on the scheduled users in $z$-th RRB across the remaining $b' \neq b$ RRHs and the corresponding power level $P_{b',z}$. We use in this work the standard perfect modulation assumption; i.e., the reception of an uncoded/encoded file sent in the $z$-th RRB of the $b$-th RRH is successful at the $u$-th mobile user if the transmission rate $R_{b,z}$ is less than or equal the user’s capacity, i.e., $R_{b,z} \leq R_{b,z}^u$. In other words, the $z$-th RRB of $b$-th RRH can transmit at a rate at most equal to the minimum ergodic capacity of its assigned users. The set of achievable capacities of all users in all RRBs across all RRHs can be represented by the set:

$$\mathcal{R} = \bigotimes_{(b,z,u) \in \mathcal{B} \times \mathcal{Z} \times \mathcal{U}} R_{b,z}^u,$$

where the symbol $\bigotimes$ represents the product of the set of the achievable capacities.

B. Instantly Decodable Network Coding

We assume that all users are interested in receiving/overhearing files out of a set $\mathcal{F}$ containing a finite library
of $F$ files. These files are deemed popular due to their previous multiple downloads by different subsets of users. These popular files may represent any data format such as pictures, executable instructions, and frames from video-on-demand streaming, and thus a user can start playing the video after some (short) time for buffering, while download goes on. All files in $\mathcal{F} = \{f_1, f_2, \ldots, f_F\}$ are assumed to be stored in the cloud with the same size of $N$ bits so that an XOR encoding (binary operation) of any number of files, called herein encoded file, is also $N$ bits. Furthermore, the cloud keeps a log of all downloaded files by each user. Each RRH holds the whole set of files $\mathcal{F}$ that they receive from the cloud controller.

We assume that various RRBs in the same RRH can cooperate by sending different parts of the same uncoded/encoded file, i.e., the fragmentable constraint is allowed in this paper. Therefore, during a single transmission, users can get their requested files from the same RRH by listening to one or various RRBs. From a security perspective, the cloud controller multiplexes users to RRBs in RRHs based on their requests and encodes the communication. As such not possible for other users or attackers to decode the transmission.

The previous users’ downloaded files create an asymmetric side information in the network. Indeed, in each scheduling epoch, the files of $\mathcal{F}$ can be classified for each user $u$ as follows.

- The Has set $\mathcal{H}_u$ containing files previously downloaded by the $u$-th user.
- The Wants set $\mathcal{W}_u = \mathcal{F}\setminus \mathcal{H}_u$ containing files requested by the $u$-th user in the current scheduling frame.

The cloud controller exploits such side information diversity to transmit encoded files in order to maximize the number of successfully received bits, i.e., throughput, in each scheduling frame. IDNC allows the cloud to generate XOR-encoded files using the source files in $\mathcal{F}$. Let $\tau_{bz}(\kappa_{bz})$ denotes the targeted set of users benefitting from the encoded file $\kappa_{bz}$ transmitted from the $z$-th RRH in the $b$-th RRH, where $\kappa_{bz}$ is an element of the power set $\mathcal{P}(\mathcal{F})$. A combination $\kappa_{bz}$ can be used to extract a new wanted file by any user $u$, i.e., instantly decodable combination, if and only if

1. $R_{bz} \leq R_{bz}^u$: The user can properly decode the combination.
2. $|\mathcal{W}_u \cap \kappa_{bz}| = 1$: The user can XOR the combination $\kappa_{bz}$ with files already downloaded to retrieve a new file.

To illustrate the above mentioned concepts, consider the example in Figure 3 which illustrates a CRAN system composed of 3 users, 2 RRHs, and 1 RRH per RRH frame. Each user in this example received 2 files and missed/wants 1 file. Assuming that the achievable capacities of all users to the RRHs is 1 bit/second. Thanks to its coding ability, IDNC is expected to significantly outperform the uncoded schemes. Clearly, one possible solution is that RRH 1 targets $u_1$ and $u_2$ by sending the file combination $f_1 \oplus f_2$, and RRH 2 targets $u_3$ by sending $f_3$. Thus, the file combination $\kappa_{11} = f_1 \oplus f_2$ in RRH 1 is instantly decodable for users $u_1$ and $u_2$, i.e., $u_1, u_2 \in \tau_{11}(\kappa_{11})$, and the uncoded file $\kappa_{21} = f_3$ in RRH 2 is instantly decodable only for $u_3$, i.e., $u_3 \in \tau_{21}(\kappa_{21})$.

### III. PROBLEM FORMULATION AND GRAPH CONSTRUCTION

This section first formulates the joint scheduling and power adaptation optimization problem in CRANs of interest in this paper. Afterward, the section constructs CRAN-IDNC graph by designing and merging the power control subgraph of each RRH in the system. The presented concepts are illustrated using as an example presented in Figure 3.

#### A. Problem Formulation

As stated earlier, the paper aims to improve the overall throughput in the aforementioned CRAN setting by assigning users to the RRBs of RRH and adapting the power levels under the following network connectivity constraints (CC):

- **CC1**: Each mobile user can connect to at most one RRH, but possibly to many RRBs in that RRH.
- **CC2**: Each power level PL is bounded by a nominal maximal value.

Let $X_{bz}^u$ be a binary variable that is equal to 1 if user $u$ is assigned to the $z$-th RRH of the $b$-th RRH, and zero otherwise. Let $Y_{bz}^u$ be a binary variable that is set to 1 if user $u$ is assigned to the $b$-th RRH, and zero otherwise. The joint coordinated scheduling and power allocation problem can be formulated as follows:

$$\max_{b \in \mathcal{B}} \sum_{z \in \mathcal{Z}} \sum_{u \in \mathcal{U}} X_{bz}^u \log_2(1 + \text{SINR}_{bz}^u(P))$$  \hspace{1cm} (4a)

s.t. \hspace{0.5cm} Y_{bz}^u = \min_{z} \left( \sum_{u} X_{bz}^u, 1 \right), (b, u) \in \mathcal{B} \times \mathcal{U},  \hspace{1cm} (4b)

$$\sum_{b} Y_{bz}^u \leq 1, u \in \mathcal{U},$$  \hspace{1cm} (4c)

$$\tau_{bz}(\kappa_{bz}) = \left\{ u \in \mathcal{U} \mid \mathcal{W}_u \cap \kappa_{bz} = 1 \& R_{bz} \leq R_{bz}^u \right\},$$  \hspace{1cm} (4d)

$$0 \leq P_{bz} \leq P_{bz}^{\max}, (b, z) \in \mathcal{B} \times \mathcal{Z},$$  \hspace{1cm} (4e)

$$X_{bz}^u, Y_{bz}^u \in \{0, 1\}, \kappa_{bz} \in \mathcal{P}(\mathcal{F}), (u, b, z) \in \mathcal{U} \times \mathcal{B} \times \mathcal{Z},$$  \hspace{1cm} (4f)
where the optimization is carried over the variables $X_z^u$, $Y_z^u$, $\kappa_{bz}$, $R_{bz}$, and $P_{bz}$. The variables $X_z^u$ and $Y_z^u$ are discrete optimization parameters that represent the user-RRH and user-RRB associations, respectively. On the other hand, the variables $\kappa_{bz}$, $R_{bz}$ and $P_{bz}$ account for the file combination, the transmission rate, and the PLs for the $z$-th RRB of the $b$-th RRH, respectively. Constraints (4b) and (4c) translate CC1. Consequently, (4a) ensures that all users belonging to these targeted sets $\tau_{bz}(\kappa_{bz})$ $\forall b \in B$ and $z \in Z$ must receive an instantly decodable transmission. Finally, (4e) corresponds to constraint CC2.

The optimization problem (4a) is a mixed discrete (user scheduling) and continuous (power allocation) optimization problem. Therefore, computing its global solution may need an extensive search over all possible user-to RRB/RRH associations, and determining the PL for each RRB which is not feasible for any reasonably sized network. Inspired by the work in [7], this paper provides an efficient optimal solution to (4a) by designing a discrete set of PLs, i.e., replacing the $X_z^u$ and $Y_z^u$ by the set of all possible associations. Therefore, computing its global solution may need an extensive search over all possible user-to RRB/RRH associations, and determining the PL for each RRB which is not feasible for any reasonably sized network.

As a result, each vertex $v \in \mathcal{V}^\phi$ represents the partial schedule of users to the $z$-th RRB across all connected RRHs. The construction of the set of all vertices $\mathcal{V}^\phi$ relies on the fact that the merged associations can be served simultaneously. Therefore, each $v \in \mathcal{V}^\phi$ representing the association $\mathcal{S}$ satisfies the following conditions:

- **LC1:** For all $(s, s') \in \mathcal{S}$ such that $\varphi_u(s) = \varphi_u(s')$, we have $\varphi_f(s) = \varphi_f(s')$. This condition guarantees that all associations in the same RRB $z$ and RRH $b$ have the same transmission rate.
- **LC2:** For all $(s, s') \in \mathcal{S}$ such that $\varphi_b(s) \neq \varphi_b(s')$, we have $\tau \cap \tau' = \emptyset$. This condition guarantees that each user is scheduled to at most a single RRH.

Intuitively, assuming the power distribution $\mathcal{P}$ will be computed later, a vertex $v$ representing the associations $\mathcal{S} \in \mathcal{A}_z$ has a weight that reflects the total contribution of the vertex to the network, i.e., the weight of $v$ can be expressed as:

$$w(v) = \sum_{s \in \mathcal{S}} \log_2(1 + \text{SINR}_{\varphi_u(s)}(\mathcal{P}))_{\varphi_f(s)}.$$  

**C. CRAN-IDNC Graph Design**

In [7], the authors introduce the MB-RA-IDNC graph as a design to represent all possible file combinations, transmission rates, and users that can instantly decode the transmission for a multi base-station setting. This subsection extends the formulation to the more practical and promising paradigm of
The CRAN of interest in this paper. The study is further extended to include power optimization by exploiting the local power allocation graphs in a similar fashion as in [7].

The CRAN-IDNC graph, denoted by $G(V, E)$, is constructed by first generating all the $Z$ power control subgraphs. The vertex set of the CRAN-IDNC graph is simply the union of vertices of all the power control subgraphs, i.e., $V = \bigcup_{z \in Z} V^z$. Whereas edges between vertices within the same power control subgraph are already described in the previous subsection, the rest of this section describes remaining edges corresponding to different RRBs.

Following similar philosophy as before, two different vertices belonging to two different subgraphs are adjacent if their combination results in a feasible schedule. In particular, two vertices are connected if no user is scheduled to different RRBs. To mathematically formulate the above constraint, let vertex $v \in G^z$ be corresponding to the association $S$ and vertex $v' \in G^{z'}$ corresponding to the association $S'$. Vertices $v$ and $v'$ are adjacent if the associations they represent satisfy the following general condition (GC):

- **GC**: For all $(s, s') \in S \times S'$ such that $\tau \cap \tau' \neq \emptyset$, we have $\varphi_b(s) = \varphi_b(s')$. The condition insists that the same user can be scheduled only to a unique RRB.

Given the CRAN-IDNC graph $G(V, E)$ as constructed above, it can be established that any maximal clique in the graph represents a set of coded transmissions that satisfies the following criterion:

- All users, having vertices in the maximal clique, can decode a new file from the transmission schedule of all RRBs and RRHs.
- Each user is scheduled to a single RRB.
- Each RRB identified by the vertices in a maximal clique adopt the transmission rate identified by the vertex. Such rate represents the smallest channel capacity of all users served by that RRB.

Given the optimal power allocation $P$, the following theorem reformulates the joint coordinated scheduling and power allocation problem of interest in this paper.

**Theorem 1.** The CRAN coordinated scheduling and power allocation problem is equivalent to a maximum-weight clique problem over the CRAN-IDNC graph, and can be written as:

$$\arg \max_{C \in \mathcal{C}} \sum_{v \in C} w(v),$$

where $C$ is a maximal clique in the CRAN-IDNC graph, $\mathcal{C}$ is the set of all possible maximal cliques of degree $Z$, and the weight of a vertex $v \in V$ is defined in (5). The set of targeted users and the file combination of the $z$-th RRB across all RRHs is obtained by combining the vertices of the maximum clique corresponding to the power control subgraph $G^z$.\[\Box\]

**IV. JOINT SCHEDULING AND POWER ALLOCATION SOLUTION USING IDNC**

This section proposes a solution to the joint coordinated scheduling and power optimization problem in (4a). The philosophy of solution relies on solving the power control optimization problem for each vertex of the power control graph which would allow the construction of the aforementioned CRAN-IDNC graph. Afterward, using the result of Theorem 1, this section shows that the optimal throughput can be reached by investigating the maximum-weight clique in the CRAN-IDNC graph, which can be solved optimally and efficiently using low-complexity graph-theoretic algorithms that available in the literature, e.g., [19]–[21].

**A. Optimal Scheduling and Power Control Solution**

This subsection provides an efficient method for constructing a discrete set of power levels such that the optimal solution of (4a) is reached. More specifically, we show that by simultaneously computing the optimal power levels $P$ while generating the CRAN-IDNC graph, we can achieve the optimal solution of the joint coordinated scheduling and power optimization problem.

Consider the $z$-th local power control graph and a vertex $v \in V^z$ in that graph associated with the associations $S = \{s_1, s_2, \ldots, s_8\} \in A_z$, where $S$ is the degree of $S$, i.e., $S = |S|$, and $S$ represents the total targeted users of $\sum_{b \in B} |\kappa_{zb}(k_{zb})|$. The optimal power levels $P_{bz}$ that maximize the received throughput for that particular vertex $v$ are the solution to the following optimization problem:

$$\max_{P_{bz}} \sum_{b \in B} |\kappa_{zb}(k_{zb})| \cdot \min_{u \in T_{bz}(k_{zb})} \log_2(1 + \text{SINR}_{bz}^u(P))$$

s.t. $0 \leq P_{bz} \leq P_{bz}^{\text{max}}$, $\forall b \in B$, \hspace{1cm} (7)

where the optimization is over the power levels $p_{bz}$, $\forall b \in B$.

As stated earlier, the power level $p_{bz}$ of $z$-th RRB in the $b$-th RRH depends not only on the corresponding power levels $p_{bw}$ and on the scheduled users in these RRB. The power optimization problem (7) is a well-known non-convex problem [22]. Despite the non-convexity of the problem, it can be solved efficiently using one of the efficient algorithms (e.g., [22], [23]). Our proposed solution can use any of these power optimization algorithms to solve problem (7).

**B. Low-Complexity Greedy Algorithm**

It is well established that the maximum-weight clique problem is the one of finding the clique with the maximum-weight, which is an NP-complete problem, and even its approximation is hard [24]. However, it can be optimally solved with reduced complexity as compared to the naive search, e.g., the optimal algorithms in [20], [21]. In this work, we propose a method similar to the one in [7] to achieve the optimum of the joint coordinated scheduling and power problem (4a) for one particular transmission.

The joint coordinated scheduling and power optimization problem can be solved by first constructing the CRAN-IDNC graph as follows. For each RRB $z \in Z$, a power control subgraph $G^z$ is generated using LC1 and LC2. Afterwards,
Algorithm 1 Joint Coordinated Scheduling and Power Allocation Algorithm

Require: $\mathcal{U}, \mathcal{F}, B, Z, H_u, W_u$ and $h_{b_z}^u((u, f)) \in \mathcal{U} \times F$, 
$(b, z, c) \in B \times Z \times C$.
Initialization: maximum-weight clique $C = \phi$.

for $z \in Z$ do
  Initialization: $G^z = \phi$.
  for all $S = \{s_1, s_2, \ldots, s_k\} \in \mathcal{A}_z$ do
    Solve (8a) to compute the optimal power allocations $P = \{(p_{1Z}^1, p_{1Z}^2, \ldots, p_{BZ}^z)\}$
    Create $v = \{(s_1, r_{1Z}^1, p_{1Z}^1), \ldots, (s_k, r_{1Z}^k, p_{1Z}^k)\}$
    \[ \ldots \{(s_B, r_{BZ}^B, p_{BZ}^z)\}\}$.
    Calculate $w(v)$ using (5).
    Set $G^z = G^z \cup \{v\}$.
  end for

end for

Set $G = \bigcup_{z \in Z} G^z$.
Connect vertices of $G$ using GC.
Solve maximum-weight clique problem over $G$.
Output $C$

for each RRB $z \in Z$ across all RRHs, a vertex $v \in G^z$ corresponding to the feasible schedule $S \in \mathcal{A}_z$ is generated for all possible associations. The optimal PLs of each association are, then, calculated by solving the optimization problem (7).
The vertex in the power control subgraph $G^z$ is generated by appending the computed PLs and the corresponding rates to that vertex as shown in Section IV-A. The same steps above are repeated for all RRBs $z \in Z$. The CRAN-IDNC graph is then, designed by merging all subgraphs and adding connections according to GC. The optimal solution to the joint coordinated scheduling and power optimization problem is found by solving the maximum-weight clique problem in CRAN-IDNC graph in which each iteration of finding the maximum-weight clique is implemented as follows. The algorithm computes the weight using (5), then the vertex with the maximum-weight $v^*$ is selected and added to $C$, i.e., $C$ is initially empty. The graph $G$ is, then, updated by eliminating the selected vertex $v^*$ and all the vertices that are not adjacent to it so that to guarantee that the next selected vertex is not in feasible transmission conflict with the already selected ones in $C$. The process continues until no more vertices exist in $G$. Clearly, the number of vertices in the selected maximum-weight clique is $Z$. The detailed procedures of the algorithm are provided in Algorithm 1.

C. Motivating Example

Through many steps, this subsection illustrates how to use Algorithm 1 to construct the CRAN-IDNC graph shown in Figure 4 of the example presented in Figure 3.

First step: In this step, we first generate the set of all possible associations $\mathcal{M} = \{u_1f_1, u_2f_2, u_3f_3\}$. Then, based on the instant decodability conditions, i.e., C1 and C2 that explained in Section III-B we generate all IDNC file combinations $\mathcal{C}$. Table II summarizes all possible IDNC combinations.

**Table II**

| $c_i(k, \tau)$ | $1$ | $2$ | $3$ | $4$ | $5$ | $6$ | $7$ |
|----------------|-----|-----|-----|-----|-----|-----|-----|
| $((f_1 \oplus f_2), (u_1, u_2))$ | $(f_1, (u_1))$ | $(f_1 \oplus f_3, (u_1, u_3))$ | $(f_2, (u_2))$ | $(f_2 \oplus f_3, (u_2, u_3))$ | $(f_3, (u_3))$ | $((f_1 \oplus f_2 \oplus f_3), (u_1, u_2, u_3))$ |

**Table III**

| $S_i$ | $S_j$ |
|-------|-------|
| $[111] R, 21 c_6 R]$ | $[111] R, 21 c_6 R]$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ |
| $2 * r_{11} + r_{21}$ | $2 * r_{11} + r_{21}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ |
| $3 * r_{11}$ | $3 * r_{11}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ |
| $2 * r_{11} + 2 * r_{21}$ | $2 * r_{11} + r_{21}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2111 r_{11} p_{11}]$ | $[111] r_1 p_1, 2122 r_{11} p_{11}, 2111 r_{11} p_{11}]$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2111 r_{11} p_{11}]$ | $[111] r_1 p_1, 2122 r_{11} p_{11}, 2111 r_{11} p_{11}]$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2111 r_{11} p_{11}]$ | $[111] r_1 p_1, 2122 r_{11} p_{11}, 2111 r_{11} p_{11}]$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ |

**Table IV**

| $r_i$ | $u_i$ |
|-------|-------|
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $2 * r_{11} + r_{21}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $2 * r_{11} + r_{21}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $3 * r_{11}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $2 * r_{11} + 2 * r_{21}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $2 * r_{11} + r_{21}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $2 * r_{11} + r_{21}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $2 * r_{11} + r_{21}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $2 * r_{11} + r_{21}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $2 * r_{11} + r_{21}$ |
| $[111] r_1 p_1, 2122 r_{11} p_{11}, 2133 r_{21} p_{21}]$ | $2 * r_{11} + r_{21}$ |

Second step: This step generates all feasible schedules $S \in \mathcal{A}_z$ such that each schedule consists of many associations.
Lemma 1. The complexity of finding the optimal solution of (4a) based on Algorithm 1 is \(O(c^2P_BZ^2 + cP_BZ + 1 + Z)\), where \(c^2P_B = \frac{n!}{(n-k)!}\) is the number of permutations, and \(c(x)\) is the computational complexity of solving the power allocation problem \(\{7\}\) with \(x\) variables.

Proof. The complexity of the heuristic solution using Algorithm 1 can be decomposed in the complexity of constructing the CRAN-IDNC graph and the complexity of solving the maximum-weight clique over that graph.

We can construct the CRAN-IDNC graph by first looking at the complexity of generating a single subgraph, i.e., power control subgraph. It can be noted that the number of vertices in each subgraph is the total number of possible associations \(|S|\), and the number of associations relies on all possible IDNC file combinations \(C\). Since each subgraph is created for each \(z\)-th RRB across \(B\) RRHs, the total number of the associations \(S\) in each subgraph is \(c^2P_B\). From Section III-B it is clear that each association is represented by a vertex \(v\), then, the complexity of generating the total number of vertices in each subgraph \(O(c^2P_B)\). From Section IV-A we run the power optimization \(\{7\}\) \(c^2P_B\) times to calculate the optimal power allocations for each vertex in the power control subgraph. Hence, the complexity of constructing a subgraph and solving the power optimization is \(O(c^2P_Bc(A))\).

Before computing the maximum-weight complexity, we need first to build the adjacency matrix of the whole (CRAN-IDNC) graph. In other words, we need to check the General Condition (GC) of each pair of the total number of vertices in CRAN-IDNC graph \(O(c^2P_BZ)\) to determine whether they should be connected with an edge, thus needing \(O(c^2P_BZ)^2\). The complexity of the maximum-weight clique algorithm can be decomposed in sum weights and vertex search computations as follows. Each iteration needs \(O(c^2P_BZ)\) operations for weight calculations of its maximum-weight clique. Note that each maximum-weight clique has at most \(Z\) vertices as each subgraph can contribute at most with one vertex per transmission. Indeed, the complexity of the algorithm for identifying the maximum-weight clique and their sum weights requires at most \(O(c^2P_BZ + Z)\). Given the above configurations on the complexities of the different algorithm components, the total complexity of Algorithm 1 for each transmission is \(O(c^2P_BZ^2 + c^2P_BZ + 1 + Z)\) operations. Therefore, the total computing complexity of Algorithm 1 is \(O(c^2P_BZ^2 + c^2P_BZ + 1 + Z)\).

It can be noted that the optimal joint solution needs a higher computational complexity. Thus, Section V proposes the decoupling approach to efficiently approximate the joint solution.

V. ITERATIVE OPTIMIZATION FOR COORDINATED SCHEDULING AND POWER CONTROL

In this section, we present an iterative coordinated scheduling and power control policy to solve the optimization problem \(\{4a\}\). In other words, for a fixed PL, the coordinated scheduling problem is addressed, and for a fixed scheduling, the power control problem is solved. The solution requires that the cloud collects and processes the coordinated scheduling and power control levels. The iteration between these two problems is carried out upon convergence.

To solve \(\{4a\}\), notice first that for a given feasible power levels PLs, the joint optimization problem \(\{4a\}\) can be simplified to a coordinated scheduling problem only, and can be
expressed as follows:

\[
\max_{b \in B, z \in Z} \sum_{u \in \tau_{b_2}(\kappa_{b_2})} X^u_{b_2} R_{b_2} \quad (8a) \\
\text{s.t. } Y^u_b = \min \left( \sum_z X^u_{b_2}, 1 \right), \quad \forall (b, u) \in B \times U, \quad (8b) \\
\sum_b Y^u_b \leq 1, \quad \forall u \in U, \quad (8c) \\
\tau_{b_2}(\kappa_{b_2}) = \left\{ u \in U \mid \kappa_{b_2} \cap W_u = 1 & R_{b_2} \leq R^u_{b_2} \right\}, \quad (8d) \\
X^u_{b_2}, Y^u_b \in \{0, 1\}, \quad \kappa_{b_2} \in \mathcal{P}(\mathcal{J}), (u, b, z) \in U \times B \times Z. \quad (8e)
\]

The optimization is carried over the variables \(X^u_{b_2}, Y^u_b, \kappa_{b_2}\) and \(R_{b_2}\). The variables \(X^u_{b_2}\), \(Y^u_b\), and \(R_{b_2}\) is continues optimization parameter. Constraints (8b) and (8c) translate the system condition (CC1), i.e., each user must connect to at most one RRB but possibly to many RRBs within the same RRH frame. In order to efficiently solve (8a), this paper uses graph theory techniques to map the feasible points to maximum cliques in a coordinated scheduling graph as explained in Section V-A.

On the other hand, for any given user-RRBs/RRHs coordinated scheduling, the joint problem (4a) can be considered as a power allocation step and reduces on a per-RRB basis. For each RRB \(z\), the optimization problem can be written as:

\[
\max \sum_{b \in B} \sum_{u \in \tau_{b_2}(\kappa_{b_2})} \log_2 (1 + \text{SINR}^u_{b_2}(P)) \\
\text{s.t. } 0 \leq P_{b_2} \leq P^\text{max}_{b_2}, \quad \forall b \in B, \quad (9)
\]

where the optimization is over the set of powers \(P_{b_2}, \forall b \in B\), where \(B\) is the set of RRHs that have associations in the fixed schedule, and \(u\) is the index of user that belongs to the set of targeted users \(\tau_{b_2}(\kappa_{b_2})\) in the fixed schedule.

To solve (9), the corresponding optimal power levels \(P_Ls\) must satisfy the Karush-Kuhn-Tucker (KKT) condition as explained in Section V-B. Therefore, this section aims to propose an iterative solution to solve (4a) approximately.

### A. Coordinated Scheduling For Fixed Power Levels

As stated earlier, for fixed power allocation, the joint coordinated scheduling and power allocation optimization problem (4a) is reduced to a coordinated scheduling problem (8a) only. Thus, in this subsection, we solve (8a) using graph theory techniques by constructing the coordinated scheduling graph, in which each vertex represents the possible association of RRHs, users, files and achievable capacities of each RRB, and then reformulates the problem. Moreover, we use an efficient solution to solve (8a).

Let \(\mathcal{A}\) be the set of all possible associations between RRHs, RRBs, users, files, and the achievable capacity, i.e., \(\mathcal{A} = B \times Z \times U \times F \times R\). Let the coordinated scheduling graph be denoted by \(\mathcal{G}(\mathcal{V}, \mathcal{E})\) wherein \(\mathcal{V}\) and \(\mathcal{E}\) refer to the set of vertices and edges of this graph, respectively.

This graph is constructed by generating a vertex \(v\) for each possible association \(s \in \mathcal{A}\). In the same RRB \(z\) and RRB \(b\), two vertices \(v, v' \in \mathcal{V}\) associated with \(s, s' \in \mathcal{A}\) and \(v' \in \mathcal{V}\) associated with \(s' \in \mathcal{A}\) are connected by an edge if one of IDNC conditions (C1 or C2) in Section III-B and \(\varphi_r(s) = \varphi_r(s')\) are true. This satisfaction ensures that all users represented by the associations have the same transmission rate, and receive always decodable transmission.

Similarly, Two different vertices belonging to two different RRHs/RRBs are then set adjacent if their combination results in a feasible schedule, i.e., it satisfies the system constraint (CC1). Let vertex \(v \in \mathcal{G}\) be corresponding to the association \(s \in \mathcal{A}\) and vertex \(v' \in \mathcal{G}\) corresponding to the association \(s' \in \mathcal{A}\). The vertices \(v, v'\) are adjacent if one of the General Conditions (GC) is satisfied.

- **GC1**: \(\varphi_u(s) = \varphi_u(s')\) and \(\varphi_f(s) = \varphi_f(s')\), \(\forall (s, s') \in \mathcal{A}\). This condition translates the fact that the same user can be served with multiple RRBs within the same RRH.
- **GC2**: \((\varphi_u(s) = \varphi_u(s')\) and \(\varphi_f(s) = \varphi_f(s')\)) OR \((\varphi_b(s) = \varphi_b(s')\) and \(\varphi_f(s) = \varphi_f(s')\)) \(\in \mathcal{H}_{\varphi_u(s')}\). This condition guarantees that the encoded combinations of the same users can be served by multiple RRBs within the same RRH.
- **GC3**: \(\varphi_u(s) \neq \varphi_u(s')\) and \(\varphi_f(s) \neq \varphi_f(s')\). This condition completes the adjacencies in the graph for any two vertices not opposing the CC1 constraint for any two different users.

Figure 5 shows an example of the coordinated scheduling graph for a simple network consisting of 3 users, 3 files, 2 RRHs, and 1 RRB in each RRH frame. In this example, each vertex is labeled \(bzuf\), where \(b, z, u, f\) and \(r\) represent the indices of RRHs, RRBs, users, files and achievable capacities, respectively. The Dashed and solid lines in Fig. 5 represent the edges generated by the aforementioned local conditions and general conditions (C1), (C1) and GC, respectively, and the potential cliques in this example represented in the graph by solid lines are: \([1111, 21221], [21322, 1111], [11221, 11332], [21221, 11331], [1111, 11221, 11331], [21112, 11222, 11332], [11223, 21112, 21332]\) achieving a total throughputs of 2, 3, 3, 3, 3, 6, and 7 bits/sec, respectively. Clearly, the red colored vertices represent the last maximal clique, and should be the one selected as it maximizes the throughput for this scheduling frame.

Given the above coordinated scheduling ‘graph’ construction \(\mathcal{G}(\mathcal{V}, \mathcal{E})\), it can be established that any maximal clique in the graph satisfies that all users have vertices in the selected clique receive/overhear an instantly decodable transmission (satisfy XOR-IDNC and transmission rate conditions), and then can decode a new file.

The following theorem characterizes the solution to the coordinated scheduling problem for fixed power allocation.

**Theorem 2.** The coordinated scheduling problem in (8a) is equivalent to a maximum-weight clique problem over the coordinated scheduling graph, wherein the weight of a vertex \(v \in \mathcal{V}\) corresponding to the association \(s = (b, z, u, f, r) \in \mathcal{A}\) is given by

\[
w(v) = r. \quad (10)
\]

**Proof.** This theorem can be proved by demonstrating the following facts. The first fact establishes a one-to-one mapping between the feasible schedules and the cliques in the coordinated scheduling graph. Afterward, the weight of each
Algorithm 2 Coordinated Scheduling Algorithm

Require: $U, F, B, H_u, W_u, P_{bz}, R$ and $h_{bz}^u$.

(b, z, u, f) $\in B \times Z \times U \times F$.

Initialization: maximum-weight clique $M = \phi$.

Construct $G$ using $(V, A)$.

Solve maximum-weight clique problem over $G$ as follows:

while $G \neq \phi$ do
    \begin{itemize}
        \item Select $v^* = \arg\max_{v \in G} \{w(v)\}$
        \item Set $M = M \cup v^*$
        \item Set $G = G(v^*)$
    \end{itemize}

Continue only with the vertices adjacent to $v^*$

Output $M$

vertex is set to be the contribution of the corresponding user to the network. Therefore, the maximum weight clique is a feasible solution with the maximum received-throughput. In other words, the maximum weight clique is the solution to (8). The complete proof can be found in Appendix A in [1].

In [24], it is shown that the maximum-weight clique problem is NP-hard. However, it is established that it can be optimally solved with reduced complexity as compared to the $O(|V|^2|V|)$ naive exhaustive search methods, e.g., the optimal algorithms in [19]–[21]. The maximum-weight clique problem can be solved in linear time with respect to its size using the simple heuristic proposed shown in Algorithm 2.

B. Power Allocation For Fixed Schedule

The power allocation step assumes a fixed user-RRB/RRH schedule and finds the optimal power levels $P_L$ of each RRB in (9). It can be easily noted that (9) is a well known non-convex optimization problem, and its global solution is not feasible. Thus, the remaining of this section focuses on the numerical solution to achieve at least a local optimum solution. Therefore, our focus in this section is to solve the optimization problem (9) using the Karush-Kuhn-Tucker (KKT) iteration approach. In particular, for a given user-RRB/RRH selection, the corresponding optimal set of powers must satisfy the first derivative, i.e., KKT condition. Therefore, the objective function of the problem (9) which is optimized over the set of power on a RRB-by-RRB basis, can be expressed as:

$$R(P_{z_1}^z, P_{z_2}^z, ..., P_{z_B}^z) =$$

$$\sum_{b \in B} \sum_{u \in \tau_b(k_{bz})} \log_2 \left( 1 + \frac{P_{bz}^u |h_{bz}^u|^2}{\sigma^2 + \sum_{b' \neq b} P_{b'z}^u |h_{bz}^{u'}|^2} \right)$$

s.t. $0 \leq P_{bz} \leq P_{bz}^{max}, \ \forall \ b \in B.$

We start by taking the first derivative of the objective function (11) with respect to $P_{bz}$:

$$\frac{\partial R}{\partial P_{bz}} = \frac{\partial}{\partial P_{bz}} \sum_{u \in \tau_b(k_{bz})} \log_2 \left( 1 + \frac{P_{bz}^u |h_{bz}^u|^2}{\sigma^2 + \sum_{b' \neq b} P_{b'z}^u |h_{bz}^{u'}|^2} \right)$$

$$+ \frac{\partial}{\partial P_{bz}} \sum_{b' \neq b} \sum_{u \in \tau_{b'}(k_{b'z})} \log_2 \left( 1 + \frac{P_{b'z}^u |h_{bz}^{u'}|^2}{\sigma^2 + \sum_{b'' \neq b} P_{b''z}^u |h_{bz}^{u''}|^2} \right)$$

$$= \frac{1}{P_{bz}} \sum_{u \in \tau_b(k_{bz})} \left( \frac{\text{SINR}_{bz}^u}{1 + \text{SINR}_{bz}^u} \right)$$

$$- \sum_{b' \neq b} \sum_{u \in \tau_{b'}(k_{b'z})} \frac{|h_{bz}^{u'}|^2}{P_{b'z}^u |h_{bz}^{u'}|^2} \left( \frac{\text{SINR}_{b'z}^u}{1 + \text{SINR}_{b'z}^u} \right)$$

(12)

where,

$$\text{SINR}_{bz}^u = \left( 1 + \frac{P_{bz}^u |h_{bz}^u|^2}{\sigma^2 + \sum_{b' \neq b} P_{b'z}^u |h_{bz}^{u'}|^2} \right)$$

and $u \in \tau_b(k_{bz})$ and $u' \in \tau_{b'}(k_{b'z})$ are the scheduled users of the $b$-th RRH, and the $b'$-th RRH at the $z$-th RRB for $\forall \ b$ and $b' \in B$, respectively. By letting the above gradient equal to zero and by manipulating the optimality condition, one can obtain this manipulation for optimizing the power:

$$\frac{1}{P_{bz}} \sum_{u \in \tau_b(k_{bz})} \left( \frac{\text{SINR}_{bz}^u}{1 + \text{SINR}_{bz}^u} \right)$$

$$= \sum_{b' \neq b} \sum_{u \in \tau_{b'}(k_{b'z})} \frac{|h_{bz}^{u'}|^2}{P_{b'z}^u |h_{bz}^{u'}|^2} \left( \frac{\text{SINR}_{b'z}^u}{1 + \text{SINR}_{b'z}^u} \right)$$

(14)

Therefore,

$$P_{bz} = \frac{1}{\sum_{b' \neq b} \sum_{u \in \tau_{b'}(k_{b'z})} \frac{|h_{bz}^{u'}|^2}{P_{b'z}^u |h_{bz}^{u'}|^2} \left( \frac{\text{SINR}_{b'z}^u}{1 + \text{SINR}_{b'z}^u} \right)}$$

(15)

The KKT condition (13) is essentially a water-filling condition if the dominator term is fixed. In this case, (15) gives the following power update equation, i.e., KKT method: (for more details see [4], [25] and references therein).

$$P_{bz, new} = \left[ \frac{1}{\sum_{u \in \tau_b(k_{bz})} \left( \frac{\text{SINR}_{bz}^u}{1 + \text{SINR}_{bz}^u} \right)} \right] P_{bz}^{max}$$

(16)

where,

$$t_{b'z} = \sum_{u \in \tau_{b'}(k_{b'z})} \frac{|h_{bz}^{u'}|^2}{P_{b'z}^u |h_{bz}^{u'}|^2} \left( \frac{\text{SINR}_{b'z}^u}{1 + \text{SINR}_{b'z}^u} \right)$$

(17)

It is important to note that, the nominator in the right hand
side of $[16]$ represents the effect power of $z$-th RRB in $b$-th RRH on all corresponding RRHs in the schedule, i.e., it is the derivative of the $b$-th RRHs terms with respect to the $z$-th RRB power in the $b$th RRH. In other words, it summarizes the interfering effect of $P_{b,z}$ on the $b$-th RRH. Moreover, it depends on the transmit power, SINR and the ratio of the direct and the interfering channel gains. The dominator in the right hand side of $[16]$ shows the effect of the combined noise and interference in RRB $z$ of the RRH $b$.

C. Proposed Iterative Algorithm

To summarize the iterative solution in this section, for fixed power, we solve the coordinated scheduling problem as explained in Section V-A and Algorithm 2. Afterwards, for a fixed schedule, the power allocation problem is solved as in Section V-B and updated based on $[16]$. The Process of iterating between coordinated scheduling and power allocation steps continue until convergence. Neither the coordinated scheduling step nor the power allocation step is nondecreasing in the optimization objective. Therefore, the iterations converge.

VI. SIMULATION RESULTS

This section shows the performance of the proposed solutions in the downlink of a C-RAN described in Section II. The network model and the physical layer model are implemented in MATLAB. The total number of RRHs is fixed to 3. Users are uniformly distributed within the cell. To study the performance of the proposed algorithms in various scenarios, number of users, number of RRBs per each RRH frames, maximum power $P_{\text{max}}$, cell size $C$, and distribution of the side information vary so as to study multiple scenarios. The additional simulation parameters are summarized in Table V.

The performance of the proposed solution is compared to the state-of-the-art coded and uncoded methods. In particular, the implemented schemes in this paper are:

- **Classical IDNC (rate-unaware scheme):** This scheme jointly optimizes the selection of an XOR file combination for each RRB in each RRH without considering the achievable capacities of users. After the file selection process, the CRAN’s physical-layer employs the minimum achievable capacity of all users targeted by each RRB as its transmitting rate.

- **RLNC (rate-greedy scheme):** In this scheme, each user is associated with a single RRB to which it has the maximum capacity. If more than one user is associated with the same RRB, random linear network coding (RLNC) is employed. The encoding is done irrespectively of the side information. Indeed, as stated earlier, RLNC mixes all files with different random coefficients. The selected transmission rate in each RRB is the capacity of users having the minimum achievable capacity in that RRB.

- **Maximum power transmission scheme:** In this scheme, the transmission power of the RRBs is set to the maximum power levels $P_{\text{max}}$.

- **Joint coordinated scheduling and power control (uncoded scheme):** In this scheme, only one user is served in each RRB, each user can be assigned to more than one RRBs from the same RRH. The user-RRB association is proposed in [7] so as to maximize the sum rate of the CRAN.

- **CRAN-IDNC (rate-aware scheme):** This scheme is described in Section IV.

- **Iterative coordinated scheduling and power allocation (rate-aware scheme):** This scheme is described in Section V.

Figure 6 depicts the average throughput in bits/user/Hz achieved by our proposed algorithms and the aforementioned schemes for different numbers of users $U$, given a CRAN composed of 2 RRBs per RRH’s frame, a file size $F = 1$ Mb, a maximum transmit power $P_{\text{max}} = -42.60$ dBm, and a cell size $C = 500$m. From the figure, we note that our proposed CRAN-IDNC scheme outperforms the iterative and the other schemes. In particular, the joint optimal uncoded scheme only focuses on the high achievable rates at the expense of transmitting at most one file to a single user from each RRB in all RRHs, i.e., a maximum number of targeted users is $Z_{\text{tot}}$. On the other hand, the maximum power and the RLNC schemes serve a good number of users in each transmission but sacrifice the optimality of the power and the rate. One can also notice that the gap between our proposed scheme and the other schemes increases as the number of users increases. The gain is due to the fact that the proposed scheme benefits from the increasing number of users by mixing the flows of more and more users to the same RRB plus the role of the CRAN-IDNC scheme as an interference mitigating technique that increases with the increase in the number of users.

Figure 7 shows the average throughput in bits/user/Hz ver-
sus the numbers of RRBs $Z$ for a CRAN composed of 7 users, a file size $N = 1$ Mb, a maximum transmit power $P_{\text{max}} = -42.60$ dBm, and cell size $C = 500$m. Again, the figure shows that our proposed CRAN-IDNC scheme outperforms all other schemes. The gap in performance increases as the number of RRBs per frame grows. It can also be easily seen from the figure that the performances of both proposed schemes and the joint optimal uncoded scheme increase linearly with the increase in the number of RRBs with a fixed number of users. In fact, all schemes agree in serving the same user in different RRBs of the same RRH. Therefore, increases in the number of RRBs increases the total received throughput. It can be noted from the figure that as the number of RRBs increases our CRAN-IDNC scheme outperforms the iterative solution. This can be explained by the fact that, increasing the number of RRBs leads to more and more power control subgraphs. Thus the size of the search space becomes larger, which works in favour of our CRAN-IDNC algorithm.

Figure 8 plots the average throughput as a function of the file size $N$ in a CRAN system composed of 7 users and 2 RRBs per RRH’s transmit frame, each RRB has a maximum transmit power $P_{\text{max}} = -42.60$ dBm, and a cell size $C = 500$m. As the file’s size increases, the performance of all schemes increases. The figure shows that all schemes increase linearly with the size of the file. This can be explained by the fact that, as the size of the file increases, more and more bits are received, thus increasing the average received throughput.

Figure 9 plots the average throughput in bits/user/Hz versus the maximum power $P_{\text{max}}$, for a CRAN setting composed of 2 RRBs in each RRH frame, 7 users, a file size $N = 1$ Mb, and cell size $C = 500$m. The figure shows that our CRAN-IDNC optimization algorithm outperforms all other schemes, particularly for large maximum power. The increase in performance can be explained by the fact that as the maximum allowed power increases, the inter-RRHs interference increases, which works in favor of CRAN-IDNC algorithm as a method for interference reduction.

Figure 10 plots the average throughput in bits/user/Hz versus the cell size $C$, for a CRAN setting composed of 7 users, 2 RRBs in each RRH frames each RRB has a maximum allowed power $P_{\text{max}} = -26.98$ dBm, and a file size $N = 1$ Mb. The proposed CRAN-IDNC algorithm largely outperforms the iterative solution particularly for small cell network, i.e., high interference level. As the cell size increases, i.e., low interference level, the performance of CRAN-IDNC solution over the iterative one decreases and gains 10% improvement. Finally, despite its great merits in reducing the completion time of a frame of files in many prior works, Classical IDNC exhibits a very poor performance from a physical layer perspective, thus voiding its upper layer gains. This clearly shows the importance of rate-awareness in IDNC code design to achieve gains on both the upper and physical layers, thus leading to a real reduction in file delivery times.
Average Throughput in bits/user/Hz. Vs Cell Size

![Graph showing the average throughput in bits/user/Hz vs cell size in Km.](image)

Fig. 10. Average Throughput in bits/user/Hz. Vs Cell Size

Critical-IDNC Scheme

Classical-IDNC Scheme

RLNC Scheme

Uncoded Joint Scheme

Maximum Power Scheme

Iterative Scheme

CRAN-IDNC Joint Scheme

VII. CONCLUSION

Interference mitigation and resource blocks’ efficient exploitation in Next Generation System 5G is an emerging topic of interest. This paper investigates the cross-layer optimization in cloud-enabled networks in order to solve the throughput maximization problem. Unlike previous studies that only considered the CRAN system from a physical layer perspective, we proposed to use the information available in the network to combine files using instantly decodable network coding. Therefore, the throughput maximization problem becomes the same as the problem of assigning users efficiently to the available resource blocks, choosing the file combination and the power allocations (PLs) of each under the constraint that a user can connect to at most a single remote radio head but to many resource blocks within it. A graph theoretical approach is proposed to solve the problem by designing the CRAN-IDNC graph formed by several power control subgraphs. By establishing a correspondence between the feasible solution to the problem and the cliques in the graph, the problem is shown to be equivalent to a maximum-weight clique which can be efficiently solved using state of the art methods. Simulation results show the performance of the proposed two solutions and reveal that they outperform uncoded and rate-unaware coding solutions.

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