

Received November 7, 2017, accepted December 22, 2017, date of publication January 17, 2018, date of current version March 12, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2792222

Dynamic User-Centric Clustering for Uplink Cooperation in Multi-Cell Wireless Networks

ZHE ZHANG^{1,2}, NING WANG^{1,3}, (Member, IEEE), JIANKANG ZHANG^{1,4,5}, (Member, IEEE), AND XIAOMIN MU¹

¹School of Information Engineering, Zhengzhou University, Zhengzhou 450001, China

²School of Computer and Communication Engineering, Zhengzhou University of Light Industry, Zhengzhou 450001, China

³Department of Electrical and Computer Engineering, McMaster University, Hamilton, ON L8S 4L8, Canada

⁴National Mobile Communications Research Laboratory, Southeast University, Nanjing 210096, China

⁵School of Electronics and Computer Science, University of Southampton, Southampton SO17 1BJ, U.K.

Corresponding author: Ning Wang (ningw@ece.ubc.ca)

This work was supported in part by the National Natural Science Foundation of China under Grant 61401402, Grant 61571401, and Grant 61771431, in part by the Open Research Fund of National Mobile Communications Research Laboratory, Southeast University, under Grant 2016D02, and in part by the Outstanding Young Talent Research Fund of Zhengzhou University under Grant 1621318001.

ABSTRACT In this paper, dynamic user-centric cell clustering, which is capable of exploiting dynamics in the channel states, is investigated for joint intra-cluster interference cancellation in a multi-cell environment. A resource efficient cluster size minimization problem is formulated to dynamically group the cells into clusters based on user channel states such that quality-of-service provisioning for cell-edge users can be improved. The integer programming problem depends largely on the intra-cluster interference weight. A subgradient algorithm is employed to solve the relaxed problem when no constrain on cooperation cost is present. To reduce extra burden on backhaul due to base station (BS) cooperation, constraints on the number of per-BS cooperative links and the maximum user-centric cluster size are introduced to the optimization problem, which is solved efficiently by a greedy algorithm. Numerical results show that the proposed dynamic user-centric clustering algorithms achieve significant improvements over existing static and fixed-size dynamic clustering schemes in terms of cell-edge performance and backhaul efficiency. The proposed greedy algorithm, in particular, can effectively alleviate the overall and per-BS cooperation cost while guaranteeing the cooperative gain. With similar resource consumption and outage performance, the proposed scheme achieves 12.6% higher rate gain compared with existing fixed size dynamic clustering strategy.

INDEX TERMS Channel state information, cooperative receiving, dynamic clustering, inter-cell interference, QoS provisioning, user-centric.

I. INTRODUCTION

Inter-cell interference (ICI), which is induced by aggressive frequency reuse in multi-cell cellular wireless systems, may lead to severe performance losses in system throughput and quality-of-services (QoS) of cell-edge users. In densely deployed cellular networks, ICI is one of the key factors that limits the system capacity/throughput [1]. Multi-cell cooperative processing (MCP), also known as coordinated multipoint (CoMP) in some recent cellular standards, has been recognized as a promising technique that effectively mitigates ICI [2]. The notion of MCP is in general referred to as any kind of multi-node interference management scheme. In recent literatures, it usually has a focus on multi-cell joint signal processing. In the uplink of multi-cell wireless systems, cooperative receiving is a typical MCP scheme,

where multiple base stations (BSs) jointly receive and process signals to achieve macro diversity and interference cancellation [3]. Even though full cooperation among all the BSs in multi-cell networks can achieve the highest possible cooperative gain [1], partial cooperation among clustered cells is more practical in real applications when overhead cost of cooperation is considered. Cooperation cost for MCP operations mainly takes into account the information exchange among cooperating BSs, extra synchronization and channel estimation requirements, as well as the delay and computational complexity imposed by cooperative receiving [2], [4], [5]. The cooperation cost is sensitive to the number of cells involved in the cooperation and the inter-cell distance, both of which rely heavily on the clustering strategy. Because the BSs consume more than half of the total energy

in typical cellular networks [6], it is crucial to properly design clusters for cooperative receiving such that *green communications* can be achieved. In addition, in future ultra dense cellular networks, the backhaul crunch is of great importance to resource and interference management [7]. Considering the power consumption, backhaul occupation, as well as complexity in signal processing, the tradeoff between the gain and the cost of cooperation must be carefully addressed in the clustering strategy design.

Generally there are two categories of cell clustering strategies, namely *static clustering* and *dynamic clustering*. The static schemes pre-define clusters according to system information such as radio access network (RAN) architecture and locations of BSs. Even though typically having low complexity, static clustering achieves only limited cooperative gains because dynamics in the wireless channels are not captured [8], [9]. Dynamic clustering, on the other hand, can periodically reconfigure clusters by considering wireless fading channel states in the design problem. As a result, fading dynamics can be exploited to achieve higher cooperative gains at the cost of increased complexity. Dynamic grouping of uplink user equipments (UEs) for joint detection was proposed in [10]. Dynamic clustering algorithms based on the knowledge of channel state information (CSI) were studied for the uplink and downlink in [11] and [12], respectively. Compared with static clustering, the proposed algorithms achieved improved fairness and higher gains on sum-rate with higher complexity. Yoon *et al.* [13], focused on QoS provisioning for cell-edge UEs, and a maximum coordination gain based clustering algorithm was developed. To reduce complexity of dynamic clustering but still reap the benefits of exploiting channel dynamics, semi-dynamic strategies are proposed by limiting the choices to predefined static clusters [14]. It is noted that all the aforementioned cell clustering algorithms adopted the network-centric approach, which divides the network into non-overlapping clusters. Intra-cluster interference can be effectively eliminated through cooperative processing. However, cluster-edge UEs may still experience severe inter-cluster interference.

To improve service to cluster-edge UEs, edge-specific clustering has been proposed [15], [16]. The idea of user-centric clustering conducts clustering based on channel conditions of each UE such that fairness and cluster-edge performance can be further improved. By maximizing the normalized outage capacity of each UE, user-centric adaptive clustering was studied for dense cellular networks [17]. A semi-dynamic user-centric clustering algorithm that maximizes the average net throughput of cloud-RAN downlink was proposed in [14]. The tradeoff between spectral efficiency (SE) and load balancing in downlink CoMP was studied in [18], and a constrained SE maximization problem was solved in the clustering strategy design. However, there may exist BSs with favorable conditions for many UEs such that these BSs would be selected by a relatively large number of clusters. This imposes heavy cooperation burden onto those “popular” BSs in the form of excessive power consumption

and demand for extra backhaul. Therefore, it is reasonable to consider cooperation opportunities of a particular BS as limited resources, and the clustering algorithm should take into account fairness in imposing cooperation burden onto the BSs.

It is noted that most existing cell clustering schemes focus on selection of best cooperation partners under certain constraints such that cooperative gain is maximized. A specific cluster size is usually predefined, and the BSs that maximize the cooperative gain are selected to form the cluster. For some UEs which receive strong ICI from a small number of co-channel UEs, a small cooperation cluster is sufficient to achieve satisfactory performance. Fixing the cluster size to a much greater value results in inefficient use of cooperation resources. In [19], minimization of the intra-cluster exchange of the UE data was considered, and a channel strength based clustering algorithm was proposed for the downlink. Under the average outage probability constraint, the number of cooperative BSs was minimized for different automatic repeat request (ARQ) and hybrid ARQ (HARQ) protocols [20]. Compared with clustering schemes with fixed cluster size, better tradeoff between the gain and cost due to cooperation was achieved through cluster size minimization subject to a pre-defined cooperative performance target. However, existing cell clustering designs usually assume that the resources for cooperation, e.g., power and backhaul, were sufficient, and each UE optimizes its clustering strategy independently [20]. More practical considerations should be included in cell clustering designs for MCP.

In this paper, we investigate user-centric cell clustering for uplink multi-cell wireless networks for QoS provisioning of cell-edge UEs, where efficient use of cooperation resources and fairness among BSs regarding cooperation burden are taken into consideration. The main contributions are summarized in the following.

- Resource efficient user-centric clustering (REUCC) problem is formulated as a cluster size minimization problem, which is shown to have a form of 0-1 integer programming (IP).
- By invoking the Lagrangian dual approach, approximate analytic solution to the REUCC problem can be obtained when constraints on cooperation resources are not present.
- When the cluster size per UE and the number of cooperation links per BS are constrained, a heuristic dynamic clustering algorithm based on calculation of the interference weight has been proposed.

The remainder of this paper is organized as follows. In Section II, the system model for dynamic user-centric cell clustering is presented. The optimization problem that minimizes the cluster size is formulated in Section III, and the approximate analytic solution is derived. In Section IV, constraints on the cluster size and the number of cooperation links per BS are considered, and the interference weight based heuristic dynamic user-centric clustering algorithm is

proposed. Numerical results are presented in Section V, followed by concluding remarks in Section VI.

II. SYSTEM MODEL

A multi-cell wireless network with clustered cooperative receiving for the uplink is considered in this work. The network consists of N cells, each having a single BS with K receiving antennas. Tight frequency reuse having the frequency reuse factor equal to 1 is considered. Each randomly located UE is equipped with a single transmit antenna. UEs transmitting on the same sub-carrier introduce ICI to each other. The system model is illustrated by Fig.1, where the solid lines denote signals transmitted from a UE to its serving BS, and the dashed lines denote interferences to other cells.

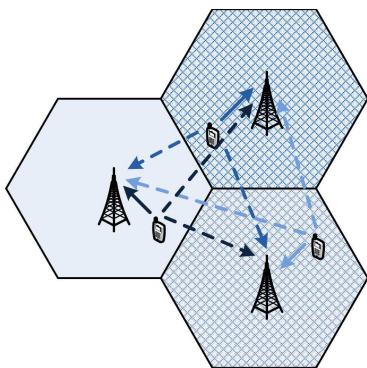


FIGURE 1. An example of the uplink ICI in a multi-cell wireless system.

Assume that the available spectrum is divided into non-overlapping sub-bands, and in any specific cell one sub-band is allocated to only one UE according to the orthogonal allocation principle to eliminate intra-cell interference. Cell clustering and cooperative receiving over all sub-carriers then reduces to multiple independent single carrier sub-problems where we determine the clustering strategy for interfering UEs on each sub-band before conducting joint processing. We therefore focus on the ICI among UE transmissions on one specific sub-carrier, i.e., the single sub-carrier case. The results can be easily extended to systems using multiple sub-carriers.

By allocating orthogonal time-frequency resources to different UEs in the same cell, each BS is the primary serving BS of one UE only. Equivalently, in the simplified single sub-carrier system model, we have one UE for each BS as the associated UE. The BS in the n -th cell is denoted as the n -th BS, and the UE operating on the target sub-carrier in the n -th cell is denoted as the n -th UE. At the n -th BS, the received signal $\mathbf{y}_n \in \mathbb{C}^{K \times 1}$ is given by

$$\mathbf{y}_n = \sum_{u=1}^N \mathbf{h}_n^u s_u + \mathbf{n}_n \quad (1)$$

$$= \mathbf{h}_n^n s_n + \sum_{u \neq n} \mathbf{h}_n^u s_u + \mathbf{n}_n, \quad (2)$$

where s_u denotes the normalized transmitted signal from the u -th UE with $\mathbb{E}[s_u^H s_u] = 1$, $\mathbf{h}_n^u \in \mathbb{C}^{K \times 1}$ denotes the channel state vector from the u -th UE to the n -th BS, and $\mathbf{n}_n \in \mathbb{C}^{K \times 1}$ is the additive white Gaussian noise (AWGN) vector with zero mean and variance σ_n^2 for each element. The first term in (2) represents the desired signal received by the n -th BS, which is transmitted by the n -th UE, and the second term denotes the ICI component from interfering UEs.

By employing the zero-forcing (ZF) linear receiver, which is of low complexity, the $1 \times K$ receiving weight vector \mathbf{w}_n at the n -th BS is given by [13]

$$\mathbf{w}_n = \left(\mathbf{h}_n^{nH} \mathbf{h}_n^n \right)^{-1} \mathbf{h}_n^{nH}. \quad (3)$$

In the multiple sub-carrier scenario, the subsequent ZF matrix can be obtained similarly by combining multiple row vectors \mathbf{w}_n s, each for one sub-carrier [11], [13].

Assume that the BS can perfectly estimate the CSI of the uplink channels from both the served UE and the interfering UEs. After individual receiving at each UE, the n -th BS is able to detect the transmitted signal s_n of the n -th UE as $\hat{s}_n^{(NC)}$, which is given by

$$\hat{s}_n^{(NC)} = \mathbf{w}_n \mathbf{y}_n \quad (4)$$

$$= s_n + \sum_{u \neq n} \mathbf{w}_n \mathbf{h}_n^u s_u + \mathbf{w}_n \mathbf{n}_n, \quad (5)$$

where the superscript (NC) denotes the non-cooperation mode.

With no cooperative receiving, the achievable rate $C_n^{(NC)}$ of the n -th UE can be derived as

$$C_n^{(NC)} = \log_2 \left(1 + \frac{1}{\sum_{u \neq n} |\mathbf{w}_n \mathbf{h}_n^u|^2 + \tilde{\sigma}_n^2} \right), \quad (6)$$

where the effective additive noise variance is given by $\tilde{\sigma}_n^2 = \|\mathbf{w}_n\|^2 \sigma_n^2$.

In the cooperation mode, the n -th UE is served by a cooperation cluster, denoted as \mathcal{G}_n , which consists of $A_n = |\mathcal{G}_n|$ BSs. The cluster \mathcal{G}_n must at least include the n -th UE's serving BS, i.e., the n -th BS. On each sub-band, cooperative receiving within a cluster is achieved by applying additional interference mitigation techniques such as successive interference cancellation (SIC) [21] and interference rejection combining (IRC) [22] at the cooperating BSs. In this work, we assume such interference mitigation is done perfectly such intra-cluster interference is completely removed. From the user-centric perspective, the above cooperative receiving process is independently done for each user within its cooperation cluster on the allocated sub-band. The information exchange for joint processing is only among BSs within a cluster, and only on the sub-band reused by the users whose serving BSs are in the cluster. This process therefore involves no information exchange among BSs on different sub-bands. As a result, after cooperative receiving, the n -th BS is able

to detect the n -th UE's transmitted signal from

$$\hat{s}_n^{(CO)} = s_n + \sum_{u \notin \mathcal{G}_n} \mathbf{w}_n \mathbf{h}_n^u s_u + \mathbf{w}_n \mathbf{n}_n, \quad (7)$$

where the superscript (CO) denotes the cooperation mode. The corresponding achievable rate $C_n^{(CO)}$ of the n -th UE in the cooperation mode is

$$C_n^{(CO)} = \log_2 \left(1 + \frac{1}{\sum_{u \notin \mathcal{G}_n} |\mathbf{w}_n \mathbf{h}_n^u|^2 + \tilde{\sigma}_n^2} \right). \quad (8)$$

III. RESOURCE EFFICIENT DYNAMIC USER-CENTRIC CLUSTERING FOR QoS PROVISIONING

From the QoS provisioning point of view, user-centric clustering and cooperative receiving should be used when the channel state between a UE and its serving BS is poor such that the QoS requirement cannot be met. An achievable rate threshold, or a received SINR threshold instead, is often adopted to specify the QoS requirement of a UE. On the other hand, because the overhead due to information exchange for cooperative processing, as well as the computational complexity of clustering algorithms, largely depends on cluster size, an efficient clustering strategy should have the cluster size as small as possible.

A. RESOURCE EFFICIENT USER-CENTRIC CLUSTERING PROBLEM FORMULATION

Updating of cell clustering can be adjusted adaptively according to each UE's mobility and channel dynamics. Typically a frame-by-frame procedure can be adopted to check if a UE experiences significant changes in its large-scale channel state such that it needs to update its cooperative cluster accordingly. In order to focus on clustering strategy design, we assume in this work that user association and scheduling are determined (dynamically) in another separate procedure before cell clustering, which results in fixed time-frequency resource allocation during the clustering period.

In user-centric clustering, each cluster is formed for a specific UE on the UE's allocated sub-band. As a result, a typical BS, either a serving BS or a cooperative BS, is possibly involved in multiple clusters for different UEs on different sub-bands. A rate threshold C_T is employed in this work as the QoS constraint, which denotes the required uplink transmission rate of the UEs.¹ For the i -th UE ($i = 1, \dots, N$), if $C_i^{(NC)} \geq C_T$, the UE experiences relatively good uplink channel state. We therefore declare this UE as a cell-centre UE, which does not require cooperative processing to guarantee the QoS provisioning. For cell-centre UEs, the single cell processing on sub-carriers allocated to cell-centre UEs is straightforward, which are excluded from the user-centric

¹Determining C_T in real applications is related to the service type and user priority of each UE. Using different values of C_T would not affect the execution of the proposed and cited clustering algorithms. For demonstration purpose, in this work we assume that all the UEs have the same QoS requirement and thus set a unified C_T for the formulated problem.

clustering process and the subsequent cooperative receiving. Conversely, if $C_i^{(NC)} < C_T$, which means the i -th UE experiences poor channel state such that the QoS requirement cannot be satisfied by the serving BS, we declare the i -th UE is a cell-edge UE which has the initiative for using cooperative processing [16]. All the cell-edge UEs in the multi-cell network form a set \mathcal{U} , which is defined as

$$\mathcal{U} = \{i \in \mathcal{U} | C_i^{(NC)} < C_T, i = 1, \dots, N\}. \quad (9)$$

The multi-cell cooperative receiving is performed distributively at each serving BS. Specifically, when a UE fails to meet the rate threshold C_T , its local serving BS initiates cooperative receiving. The BSs in this UE's cooperative cluster send their local received signals, i.e., interfering signals to this UE's uplink transmission, to this UE's serving BS. After collecting all the interfering signals within the cooperative cluster, the serving BS performs intra-cluster interference cancellation using successive interference cancellation techniques as in [21]. To achieve resource efficient clustering for cooperation, the tradeoff between cooperative gain and cost should be considered in the design objective. Consequently, in this work the cell clustering problem does not optimize performance metrics such as rate or outage probability. Alternatively, we minimize the cluster size, which is an indicator of the amount of cooperation resources involved in the joint processing, subject to rate constraints for cell-edge UEs. The notion of cooperation resources includes, but not limited to, signal processing for ICI cancellation, extra overhead for information exchange, backhaul occupation, etc. It follows from (8) that if the achievable cooperative rate of the i -th UE satisfies the rate constraint C_T , we have

$$C_i^{(CO)} = \log_2 \left(1 + \frac{1}{\sum_{j \notin \mathcal{G}_i} |\mathbf{w}_i \mathbf{h}_i^j|^2 + \tilde{\sigma}_i^2} \right) \geq C_T. \quad (10)$$

Equation (10) reveals that with fixed signal power, the uplink rate of the i -th UE achieved by user-centric clustering and cooperative processing is determined by the effective inter-cluster interference $\sum_{j \notin \mathcal{G}_i} |\mathbf{w}_i \mathbf{h}_i^j|^2$ plus the effective additive noise $\tilde{\sigma}_i^2$. The worst case is that when a UE experiences very poor channel, $\tilde{\sigma}_i^2$ alone is sufficiently large such that (10) can never be satisfied even though we include all the BSs in the network in its cooperative cluster, i.e. $\mathcal{G}_i = \{1, \dots, N\}$. A best effort solution, from the QoS provisioning perspective, is to allocate the maximum cluster $\mathcal{G}_i = \{1, \dots, N\}$ to the i -th UE to make $C_i^{(CO)}$ as close to C_T as possible.

To focus on the clustering scheme design, in the following we assume that both \mathbf{h}_i^j and σ_i^2 are known information. The effective interference terms $|\mathbf{w}_i \mathbf{h}_i^j|^2$ and the effective noise terms $\tilde{\sigma}_i^2$ can be calculated accordingly. For simplicity, we define the interference weight (IW) from the j -th UE to

the uplink of the i -th UE as

$$\Omega_i^j = \begin{cases} |\mathbf{w}_i \mathbf{h}_i^j|^2, & \text{if } j \neq i \\ 0, & \text{if } j = i. \end{cases} \quad (11)$$

With a rate constraint $C_T > 0$, (10) is equivalent to

$$\sum_{j \notin \mathcal{G}_i} \Omega_i^j \leq \frac{1}{2^{C_T} - 1} - \tilde{\sigma}_i^2, \quad (12)$$

which means that the clustered cooperative rate constraint is equivalent to requiring the inter-cluster interference to be no greater than $\frac{1}{2^{C_T} - 1} - \tilde{\sigma}_i^2$.

Denote the set of all the BSs in the network as $\mathcal{B} = \{j \in \mathcal{B} | j = 1, \dots, N\}$. In the single sub-carrier model, because each UE only has one primary serving BS, we can use cell indices for both the cell-edge UE set \mathcal{U} and the BS set \mathcal{B} , and we also have $\mathcal{U} \subseteq \mathcal{B}$. Furthermore, a binary 0-1 variable $x_{i,j}$ is introduced to denote the relationship between the j -th BS and the cluster \mathcal{G}_i of the i -th UE. When $x_{i,j} = 1$, the j -th BS belongs to \mathcal{G}_i . Conversely when $x_{i,j} = 0, j \notin \mathcal{G}_i$. The equivalent QoS constraint (12) is rewritten as

$$\sum_{j \in \mathcal{B}} x_{i,j} \Omega_i^j \geq \sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2^{C_T} - 1}. \quad (13)$$

Based on the above assumptions, we formulate the following resource efficient user-centric cell clustering (REUCC) problem $P1$ that minimizes the total cluster size in the network subject to QoS constraints for all UEs in \mathcal{U} .

$$P1: \mathcal{F}(\mathbf{v}, \mathbf{X}) = \min_{\mathbf{v}, \mathbf{X}} \sum_{i \in \mathcal{U}} \sum_{j \in \mathcal{B}} x_{i,j} \quad (14)$$

$$\text{s.t. } \sum_{j \in \mathcal{B}} x_{i,j} \Omega_i^j \geq v_i \left(\sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2^{C_T} - 1} \right), \quad \forall i \in \mathcal{U}, \quad (15)$$

$$x_{i,i} = 1, \quad \forall i \in \mathcal{U}, \quad (16)$$

$$x_{i,j} + v_i \geq 1, \quad \forall i \in \mathcal{U}, \forall j \in \mathcal{B}, \quad (17)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall i \in \mathcal{U}, \forall j \in \mathcal{B}, \quad (18)$$

$$v_i \in \{0, 1\}, \quad \forall i \in \mathcal{U}. \quad (19)$$

As defined earlier, \mathcal{U} and \mathcal{B} in $P1$ denote the set of cell-edge UEs and the set of BSs, respectively. $\mathbf{X} = \{x_{i,j}; i \in \mathcal{U}, j \in \mathcal{B}\}$ is the matrix form that include all $x_{i,j}$'s, and $\mathbf{v} = \{v_i; i \in \mathcal{U}\}$ is a 0-1 indicator variable that shows whether constraint (13) is satisfied. The notation $A_i = \sum_{j \in \mathcal{B}} x_{i,j}$ is used in subsequent sections to denote the cooperative cluster size for cell-edge UE $i \in \mathcal{U}$. When $v_i = 1$, (15) reduces into (13), and (17) is equivalent to $x_{i,j} \geq 0, \forall j \in \mathcal{B}$, which is satisfied surely because of the feasible set of $x_{i,j}$ defined by (18). When $v_i = 0$, on the other hand, it can be observed from (11) and (17) that (15) is satisfied, which further indicates that (17) is equivalent to $x_{i,j} \geq 1, \forall j \in \mathcal{B}$. We therefore have $x_{i,j} = 1, \forall j \in \mathcal{B}$ when $v_i = 0$, which is interpreted as

that for the i -th UE, if (13) can not be satisfied, the cooperative cluster \mathcal{G}_i is set to \mathcal{B} . Moreover, (16) indicates that the i -th BS, which is the primary serving BS of the i -th UE, is always included in \mathcal{G}_i .

B. REUCC PROBLEM DECOMPOSITION AND LAGRANGIAN DUAL SOLUTION

Problem $P1$ is a 0-1 integer programming problem with linear objective function and linear constraints. However, analytical solution to an IP problem is often not available due to the discrete nature of the optimization variables. In this paper, we employ the decomposition and Lagrangian dual approach to address this issue. It can be observed from $P1$ that all the constraints are independent of the index $i \in \mathcal{U}$ and the objective function. The problem $\mathcal{F}(\mathbf{v}, \mathbf{X})$ can therefore be decomposed as

$$\mathcal{F}(\mathbf{v}, \mathbf{X}) = \sum_{i \in \mathcal{U}} \mathcal{F}_i(v_i, \mathbf{x}_i), \quad (20)$$

where the row vector $\mathbf{x}_i = \{x_{i,j}; j \in \mathcal{B}\}$. The sub-problem $\mathcal{F}_i(v_i, \mathbf{x}_i)$ is formulated as

$$P1.1: \mathcal{F}_i(v_i, \mathbf{x}_i) = \min_{v_i, \mathbf{x}_i} A_i \quad (21)$$

$$\text{s.t. } \sum_{j \in \mathcal{B}} x_{i,j} \Omega_i^j \geq v_i \left(\sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2^{C_T} - 1} \right), \quad (22)$$

$$x_{i,i} = 1, \quad (23)$$

$$x_{i,j} + v_i \geq 1, \quad \forall j \in \mathcal{B}, \quad (24)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall j \in \mathcal{B}, \quad (25)$$

$$v_i \in \{0, 1\}. \quad (26)$$

The variable v_i is an integer that takes its value from $\{0, 1\}$, and it only appears in the constraints of problem $P1.1$. We therefore have

$$\mathcal{F}_i(v_i, \mathbf{x}_i) = \min \{ \mathcal{F}_i(0, \mathbf{x}_i), \mathcal{F}_i(1, \mathbf{x}_i) \}, \quad (27)$$

where $\mathcal{F}_i(0, \mathbf{x}_i)$ and $\mathcal{F}_i(1, \mathbf{x}_i)$ denote the value of $\mathcal{F}_i(v_i, \mathbf{x}_i)$ with $v_i = 0$ and $v_i = 1$, respectively. More specifically, when $v_i = 0$, we have $x_{i,j} = 1, \forall j \in \mathcal{B}$ as discussed in Section III-A. Then $\mathcal{F}_i(0, \mathbf{x}_i)$ can be rewritten as

$$P1.2: \mathcal{F}_i(0, \mathbf{x}_i) = \min_{\mathbf{x}_i} \sum_{j \in \mathcal{B}} x_{i,j} \quad (28)$$

$$\text{s.t. } x_{i,i} = 1, \quad (29)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall j \in \mathcal{B}. \quad (30)$$

It is straightforward that $\mathcal{F}_i(0, \mathbf{x}_i) = N$, where N is the cardinality of the set \mathcal{B} . In this case, $x_{i,j} = 1, \forall j \in \mathcal{B}$.

When $v_i = 1$, constraint (22) reduces to (13), and (24) is satisfied surely. We therefore have

$$P1.3: \mathcal{F}_i(1, \mathbf{x}_i) = \min_{\mathbf{x}_i} \sum_{j \in \mathcal{B}} x_{i,j} \quad (31)$$

$$\text{s.t. } \sum_{j \in \mathcal{B}} x_{i,j} \Omega_i^j \geq \sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2C_T - 1}, \quad (32)$$

$$x_{i,i} = 1, \quad (33)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall j \in \mathcal{B}. \quad (34)$$

In the extreme case when $x_{i,j} = 1, \forall j \in \mathcal{B}$, (32) reduces to

$$\tilde{\sigma}_i^2 \leq \frac{1}{2C_T - 1}. \quad (35)$$

If (35) is not satisfied, there is no solution to P1.3. We set $\mathcal{F}_i(1, \mathbf{x}_i) = +\infty$ and plug it into (27). The solution to P1.2 is the solution to P1.1 when (35) is not satisfied. When (35) is satisfied, there is at least one solution to P1.3. Since $x_{i,i} = 1$, problem P1.3 reduces to

$$\begin{aligned} P1.4 : \quad & \mathcal{F}_i(1, \mathbf{x}_i) \\ & = \min_{\tilde{\mathbf{x}}_i} \sum_{j \in \mathcal{B}} x_{i,j} + 1 \end{aligned} \quad (36)$$

$$\text{s.t. } \sum_{j \in \mathcal{B}/\{i\}} x_{i,j} \Omega_i^j \geq \sum_{j \in \mathcal{B}/\{i\}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2C_T - 1}, \quad (37)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall j \in \mathcal{B}/\{i\}, \quad (38)$$

where $\tilde{\mathbf{x}}_i = \{x_{i,j}; j \in \mathcal{B}/\{i\}\}$. A Lagrangian relaxation function can be formulated by writing down the dual of (37)

$$\begin{aligned} \mathcal{L}(\tilde{\mathbf{x}}_i, \lambda) &= \sum_{j \in \mathcal{B}/\{i\}} x_{i,j} + \lambda \left(- \sum_{j \in \mathcal{B}/\{i\}} x_{i,j} \Omega_i^j \right. \\ &\quad \left. + \sum_{j \in \mathcal{B}/\{i\}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2C_T - 1} \right) \end{aligned} \quad (39)$$

$$\begin{aligned} &= \sum_{j \in \mathcal{B}/\{i\}} x_{i,j} \left(1 - \lambda \Omega_i^j \right) \\ &\quad + \lambda \left(\sum_{j \in \mathcal{B}/\{i\}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2C_T - 1} \right), \end{aligned} \quad (40)$$

where $\lambda \geq 0$ is the Lagrangian multiplier for (37). We can further obtain the Lagrangian dual problem of P1.4 as

$$LD1.4 : \quad \max_{\lambda} d(\lambda) \quad (41)$$

$$\text{s.t. } \lambda \geq 0, \quad (42)$$

where $d(\lambda)$ denotes the Lagrangian relaxation problem of P1.4

$$LR1.4 : \quad d(\lambda) = \min_{\tilde{\mathbf{x}}_i} \mathcal{L}(\tilde{\mathbf{x}}_i, \lambda) \quad (43)$$

$$\text{s.t. } x_{i,j} \in \{0, 1\}, \quad \forall j \in \mathcal{B}/\{i\} \quad (44)$$

It can be observed from (40) that minimizing $\mathcal{L}(\tilde{\mathbf{x}}_i, \lambda)$ in LR1.4 is equivalent to minimizing $\sum_{j \in \mathcal{B}/\{i\}} x_{i,j} (1 - \lambda \Omega_i^j)$, which further implies that the solution to LR1.4 is

$$x_{i,j} = \begin{cases} 1, & \text{if } 1 - \lambda \Omega_i^j < 0. \\ 0, & \text{if } 1 - \lambda \Omega_i^j \geq 0. \end{cases} \quad (45)$$

After solving the Lagrangian relaxation problem, we further address the Lagrangian dual problem about λ . The sub-gradient method is often adopted for the search of Lagrangian multiplier, where the updating of λ is given by

$$\begin{aligned} \lambda^{(k+1)} &= P^+ \left[\lambda^{(k)} + \delta_{\lambda}(k) \left(- \sum_{j \in \mathcal{B}/\{i\}} x_{i,j}^{(k)} \Omega_i^j \right. \right. \\ &\quad \left. \left. + \sum_{j \in \mathcal{B}/\{i\}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2C_T - 1} \right) \right]. \end{aligned} \quad (46)$$

The index k represents the number of iterations, and $\delta_{\lambda}(k)$ denotes the step size used by the k -th iteration. P^+ denotes the mapping from \mathbb{R} to \mathbb{R}_+ , i.e., $P^+[\lambda] = \max(0, \lambda)$. The adaptation terminates when $d(\lambda)$ converges. Convergence is guaranteed when suitable step size and termination condition are selected [23]. Due to the weak duality of the Lagrangian dual problem, a lower bound of P1.4 can be obtained by solving LD1.4 [24]. If the solution to LD1.4 satisfies all the constraints of P1.4, the solution to LD1.4 is an optimal solution to P1.4. Otherwise, it provides an approximate (suboptimal) solution to P1.4.

Details of the IW-based unconstrained user-centric dynamic clustering algorithm (IWUC) for the REUCC problem without having per-UE or per-cell resource constraints is given in Algorithm 1. The execution of the IWUC algorithm, based on the Lagrangian relaxation procedure, requires both distributive and centralized processing. Specifically, each UE and its serving BS together determine user-centric clustering indices $x_{i,j}$ as specified by (45) in each iteration. The serving BS then reports the clustering indices to a central processing station (a lead BS in a region or a radio network controller (RNC) type equipment) through backhaul connection for the update of the dual variable λ according to (46), which will be broadcast to all the BSs for the update of $x_{i,j}$ in the next iteration. This procedure is repeated until convergence.

In Step 1 of the IWUC algorithm, the calculation of $C_i^{(NC)}$ and the comparison between $C_i^{(NC)}$ and C_T are conducted for each $i \in \mathcal{B}$, which gives a computational complexity of $\max(\mathcal{O}(N^3), \mathcal{O}(N^2K))$. Assume that the number of elements in \mathcal{U} is $M \leq N$, the computational complexity is $\mathcal{O}(MN)$ in Step 2 and Step 3, and it is $\mathcal{O}(MN^2)$ and $\mathcal{O}(M)$ in Step 4 and Step 5, respectively. To sum up, the computational complexity of the IWUC algorithm is $\max(\mathcal{O}(N^3), \mathcal{O}(N^2K))$. According to our observations in the numerical studies, convergence of the IWUC algorithm is fast.

IV. USER-CENTRIC CLUSTERING SUBJECT TO PER-UE AND PER-BS RESOURCE CONSTRAINTS

A. PER-UE AND PER-BS RESOURCE CONSTRAINTS FOR REUCC

The optimization problem **P1** aims at improving uplink rates of cell-edge UEs to satisfy the QoS constraint using minimum cooperative resources (cluster size). For UEs achieving relatively low uplink rate at the non-cooperation mode, a larger cluster is usually required for cooperative receiving to

Algorithm 1 The IW-Based User-Centric Dynamic Clustering Algorithm for REUCC Problem Without Per-UE or Per-Cell Resource Constraints (IWUC)

Step 1

- 1) Calculate $C_i^{(NC)}$ for all UEs $i = 1, \dots, N$ according to (6); if $C_i^{(NC)} < C_T$, put the i -th UE into the cell-edge UE set \mathcal{U} .
- 2) Calculate $\tilde{\sigma}_i^2$ for all $i \in \mathcal{U}$.
- 3) If $\tilde{\sigma}_i^2 > 1/(2^{C_T} - 1)$, let $v_i = 0, x_{i,j} = 1, \forall j \in \mathcal{B}, \mathcal{F}_i(0, \mathbf{x}_i) = N$; or else, go to Step 4.
- 4) Initialize the Lagrangian multiplier λ and the iteration index k , calculate $d(\lambda)$ and \mathbf{x}_i based on (43) and (45), respectively; $k = k + 1$, update λ according to (46), then update $d(\lambda)$ and \mathbf{x}_i until $d(\lambda)$ converges; obtain $\mathcal{F}_i(1, \mathbf{x}_i)$ based on \mathbf{x}_i .
- 5) Obtain the final values of (v_i, \mathbf{x}_i) according to (27). Go back to Step 2, until all UEs in \mathcal{U} finish the clustering procedure.

satisfy the QoS requirement. In extreme cases when UEs have very poor channel state, the best effort scheme requires the UE to use the maximum cluster, i.e. all the BSs in the system, to approach the QoS target, which is not efficient nor practical in real applications. We next consider constraints on the cluster size A_i for each $i \in \mathcal{U}$, and introduce an upper bound on the cluster size $A_T \leq N$

$$A_i = \sum_{j \in \mathcal{B}} x_{i,j} \leq A_T. \quad (47)$$

For each BS $j \in \mathcal{B}$, on the other hand, we denote by B_j the number of cooperative links provided by the j -th BS in cooperative receiving for cell-edge UEs in other cells. In order to balance the cooperation burden among BSs such that fairness is taken into account in the cooperation, an upper bound on the cooperative links per BS, denoted by $B_T \leq N$ is also considered. For short, B_T is referred to as the BS cooperation index in this paper.

$$B_j = \sum_{i \in \mathcal{U}/\{j\}} x_{i,j} \leq B_T. \quad (48)$$

From a cooperative resource perspective, (47) defines the maximum resource that a UE can receive, and (48) specifies the maximum resource each BS would provide. By adding (47) and (48) to problem **P1**, the REUCC problem with per-UE and per-BS resource constraints is reformulated as the follows.

$$P2 : \tilde{\mathcal{F}}(\mathbf{v}, \mathbf{X}) = \min_{\mathbf{v}, \mathbf{X}} \sum_{i \in \mathcal{U}} A_i \quad (49)$$

$$\text{s.t.} \sum_{j \in \mathcal{B}} x_{i,j} \Omega_i^j \geq v_i \left(\sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2^{C_T} - 1} \right), \quad \forall i \in \mathcal{U}, \quad (50)$$

$$\sum_{j \in \mathcal{B}} x_{i,j} \leq A_T, \quad \forall i \in \mathcal{U}, \quad (51)$$

$$\sum_{i \in \mathcal{U}/\{j\}} x_{i,j} \leq B_T, \quad \forall j \in \mathcal{B}, \quad (52)$$

$$x_{i,i} = 1, \quad \forall i \in \mathcal{U}, \quad (53)$$

$$\sum_{j \in \mathcal{B}} x_{i,j} + v_i \sum_{j \in \mathcal{B}} (1 - x_{i,j}) = A_T + v_i(N - A_T), \quad \forall i \in \mathcal{U}, \quad (54)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall i \in \mathcal{U} \text{ and } \forall j \in \mathcal{B}, \quad (55)$$

$$v_i \in \{0, 1\}, \quad \forall i \in \mathcal{U}. \quad (56)$$

Problem **P2** is also a 0-1 IP problem with linear and non-linear constraints. However, the introduction of constraint (48) couples the clustering sub-problems for each UE. Different from (17) in **P1**, this constraint (54) reduces the maximum cluster size from N to A_T such that higher efficiency can be achieved, but with a reduced level of satisfactory to the QoS requirement.

B. EFFICIENT GREEDY HEURISTIC SOLUTION FOR RESOURCE CONSTRAINED REUCC

Due to the use of the Lagrangian dual and sub-gradient method, iterative searching is incorporated in the IWUC algorithm. This leads to the high computational complexity of IWUC as pointed out in Section III-B. Compared to **P1**, solving **P2** is more involved because of the newly added coupling constraints. To reduce the computational complexity, we propose a low-complexity heuristic algorithm for **P2** in the following.

It is observed from **P2** that (52) is the only constraint that depends on i . (52) denotes that for all cell-edge UEs, the cooperation opportunities provided by each BS is limited. In order to reduce the dimension of the optimization variables in **P2**, we first sort UEs in the set \mathcal{U} and clustering for each UE is determined one by one in a queue successively. To ensure (52), after one UE determines its cooperative cluster, the remaining cooperation opportunities of each BS must be updated. The complex IP problem **P2** can thus be simplified and decomposed into a series of IP problems of one dimensional optimization variables. The following subproblem **P2.1** for the i -th UE in the processing queue is formulated as

$$P2.1 : \tilde{\mathcal{F}}_i(v_i, \mathbf{x}_i) = \min_{v_i, \mathbf{x}_i} \sum_{j \in \tilde{\mathcal{B}}^{(i)}} x_{i,j} \quad (57)$$

$$\text{s.t.} \sum_{j \in \tilde{\mathcal{B}}^{(i)}} x_{i,j} \Omega_i^j \geq v_i \left(\sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2^{C_T} - 1} \right), \quad (58)$$

$$\sum_{j \in \tilde{\mathcal{B}}^{(i)}} x_{i,j} \leq A_T, \quad (59)$$

$$x_{i,i} = 1, \quad (60)$$

$$\sum_{j \in \tilde{\mathcal{B}}^{(i)}} x_{i,j} + v_i \sum_{j \in \tilde{\mathcal{B}}^{(i)}} (1 - x_{i,j}) = A_T + v_i(\beta_i - A_T), \quad (61)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall j \in \tilde{\mathcal{B}}^{(i)}, \quad (62)$$

$$v_i \in \{0, 1\}, \quad (63)$$

where $\tilde{\mathcal{B}}^{(i)}$ represents the set of BSs which still have cooperation opportunities left when determining the cooperative cluster for the i -th UE, and β_i is the cardinality of $\tilde{\mathcal{B}}^{(i)}$. Note that $\tilde{\mathcal{B}}^{(i)} \subseteq \mathcal{B}$ because once a BS has reached the maximum number of cooperation links B_T , it must be removed from $\tilde{\mathcal{B}}^{(i)}$ to ensure that (52) is satisfied in the following clustering process for the i -th and the remaining UEs. The serving BS of the i -th UE is always in its candidate cooperative BS set $\tilde{\mathcal{B}}^{(i)}$, i.e. $x_{i,i} = 1$ is guaranteed surely.

The number of BSs in $\tilde{\mathcal{B}}^{(i)}$ depends on the sorting order of UE set \mathcal{U} , i.e. the order of the successive processing. In this work we give higher priority to cell-edge UEs having higher uplink rates at the non-cooperation mode, i.e., the UEs are sorted according to descending order of $C_i^{(NC)}$ and the user-centric clusters are determined successively according to the order by solving P2.1. It is because cell-edge UEs with lower rates without cooperation usually suffer from higher ICI or poorer channel condition, which implies that they are more likely to require

Similar to (27), for problem P2.1, we have

$$\tilde{\mathcal{F}}_i(v_i, \mathbf{x}_i) = \min \left(\tilde{\mathcal{F}}_i(0, \mathbf{x}_i), \tilde{\mathcal{F}}_i(1, \mathbf{x}_i) \right), \quad (64)$$

where $\tilde{\mathcal{F}}_i(0, \mathbf{x}_i)$ and $\tilde{\mathcal{F}}_i(1, \mathbf{x}_i)$ denote the values of $\tilde{\mathcal{F}}_i(v_i, \mathbf{x}_i)$ with $v_i = 0$ and $v_i = 1$, respectively.

When $v_i = 0$, subproblem P2.1 reduces to P2.2

$$P2.2: \quad \tilde{\mathcal{F}}_i(0, \mathbf{x}_i) = \min_{\mathbf{x}_i} \sum_{j \in \tilde{\mathcal{B}}^{(i)}} x_{i,j} \quad (65)$$

$$\text{s.t.} \quad \sum_{j \in \tilde{\mathcal{B}}^{(i)}} x_{i,j} = A_T, \quad (66)$$

$$x_{i,i} = 1, \quad (67)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall j \in \tilde{\mathcal{B}}^{(i)}. \quad (68)$$

The number of elements in $\tilde{\mathcal{B}}^{(i)}/\{i\}$ is $\beta_i - 1$. P2.2 can be solved only when $\beta_i \geq A_T$. To make $C_i^{(CO)}$ as close to C_T as possible, the $(A_T - 1)$ best candidates in $\tilde{\mathcal{B}}^{(i)}/\{i\}$, along with the i -th BS, are selected to form the i -th UE's cooperative cluster. In other words, for the $(A_T - 1)$ BSs in $\tilde{\mathcal{B}}^{(i)}/\{i\}$ with highest Ω_i^j s, $x_{i,j}$ is set to 1. Conversely, when $\beta_i < A_T$, there is no solution to P2.2. A best effort strategy similar to that discussed in Section III-B can be employed. As a result, $\tilde{\mathcal{F}}_i(0, \mathbf{x}_i) = \min(\beta_i, A_T)$.

When $v_i = 1$, subproblem P2.1 reduces to the following problem P2.3.

$$P2.3: \quad \tilde{\mathcal{F}}_i(1, \mathbf{x}_i) = \min_{\mathbf{x}_i} \sum_{j \in \tilde{\mathcal{B}}^{(i)}} x_{i,j} \quad (69)$$

$$\text{s.t.} \quad \sum_{j \in \tilde{\mathcal{B}}^{(i)}} x_{i,j} \Omega_i^j \geq \sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{2C_T - 1}, \quad (70)$$

$$\sum_{j \in \tilde{\mathcal{B}}^{(i)}} x_{i,j} \leq A_T, \quad (71)$$

$$x_{i,i} = 1, \quad (72)$$

$$x_{i,j} \in \{0, 1\}, \quad \forall j \in \tilde{\mathcal{B}}^{(i)}. \quad (73)$$

Let $\alpha_i = \min(\beta_i - 1, A_T - 1)$. A total number of α_i BSs having the α_i largest Ω_i^j in $\tilde{\mathcal{B}}^{(i)}/\{i\}$ are declared as members of $\tilde{\mathcal{A}}^{(i)}$, the set of candidate cooperative cells for the i -th UE. When $\sum_{j \in \tilde{\mathcal{A}}^{(i)}} \Omega_i^j < \sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - 1/(2C_T - 1)$, there is no solution to P2.3, so we set $\tilde{\mathcal{F}}_i(1, \mathbf{x}_i) = +\infty$. When $\sum_{j \in \tilde{\mathcal{A}}^{(i)}} \Omega_i^j \geq \sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - 1/(2C_T - 1)$, P2.3 can be solved. We first let $x_{i,i} = 1$ and $x_{i,j} = 0, \forall j \in \tilde{\mathcal{B}}^{(i)}/\{i\}$. For all $j \in \tilde{\mathcal{A}}^{(i)}$, we sort the candidate cooperative BSs according to the descending order of Ω_i^j . The j -th BS with the largest Ω_i^j in $\tilde{\mathcal{A}}^{(i)}$ is removed from $\tilde{\mathcal{A}}^{(i)}$ and selected for cooperation by setting $x_{i,j} = 1$, until $\sum_{j \in \tilde{\mathcal{B}}^{(i)}} \Omega_i^j \geq \sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - 1/(2C_T - 1)$. After determining all $x_{i,j}$ s for the i -th UE, we obtain \mathbf{x}_i and $\tilde{\mathcal{F}}_i(1, \mathbf{x}_i)$. Based on solutions to P2.2 and P2.3, we can obtain the solution to P2.1 from (64), which gives the clustering scheme for the i -th UE. The process then moves on to determine the cooperative cluster for the next UE.

The IW-based dynamic cell clustering algorithm with constraints on cooperative resources (IWCC) is summarized in Algorithm 2. The IWCC algorithm is mainly based on distributed processing at the UEs having demand for cooperation. In order to calculate Ω_i^j locally, some channel state information needs to be shared among BSs through backhaul. The computational complexity of Algorithm 2 is mainly introduced by Steps 1 through 4. The noncooperative UE rate $C_i^{(NC)}$ is calculated N times, once for each UE. These N $C_i^{(NC)}$ values are then compared with the rate threshold C_T , which gives computational complexity of $\max(\mathcal{O}(N^3), \mathcal{O}(N^2K))$. Assume there are $M \leq N$ UEs in the cell-edge UE set \mathcal{U} , the value of Ω_i^j is thus calculated $M(N - 1)$ times. In order to sort the UEs according to their IW Ω_i^j , up to M sorting operations would be required in Step 2. When the upper bound of the cluster size is less than or equal to N , i.e. $A_T \leq N$, there are N evaluations of $\sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{(2C_T - 1)}$, and up to $M(A_T - 1)$ additions and comparisons to check the constraint $\sum_{j \in \tilde{\mathcal{B}}^{(i)}} x_{i,j} \Omega_i^j \geq \sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - \frac{1}{(2C_T - 1)}$. The computational complexity is thus $\mathcal{O}(N^2K)$ from Step 2 to Step 4. Therefore the IWCC algorithm has computational complexity of $\max(\mathcal{O}(N^3), \mathcal{O}(N^2K))$. It can be observed that the computational complexity of the IWUC algorithm and that of the IWCC algorithm have the same order of magnitude. However, the iterative procedure of the IWUC algorithm would make its actual computational complexity higher than that of the IWCC algorithm.

Note that the information exchange over the backhaul for execution of the IWUC and IWCC algorithms is much lower than the backhaul resource occupation due to multi-cell

Algorithm 2 The IW-Based Dynamic Cell Clustering Algorithm for REUCC Problem Subject to Constraints on Cooperative Resources (IWCC)

Step 1

- 1) Calculate $C_i^{(NC)}$ ($i = 1, \dots, N$) for all UEs according to (6); if $C_i^{(NC)} < C_T$, put the i -th UE into the cell-edge UE set \mathcal{U} ; sort the UEs in \mathcal{U} according to the descending order of $C_i^{(NC)}$; initialize the candidate BS set $\tilde{\mathcal{B}}^{(i)}$ and the number of cooperative links B_j the j -th BS allows for all $j \in \mathcal{B}$.
- 2) For the i -th UE in \mathcal{U} , calculate Ω_i^j for all $j \in \tilde{\mathcal{B}}^{(i)}/\{i\}$, and sort them in a descending order; calculate $\alpha_i = \min(\beta_i - 1, A_T - 1)$, the BSs having the α_i largest Ω_i^j values are designated as members of the set $\tilde{\mathcal{A}}^{(i)}$.
- 3) If $\sum_{j \in \tilde{\mathcal{A}}^{(i)}} \Omega_i^j < \sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - 1/(2^{C_T} - 1)$, the cooperative cluster of the i -th UE \mathcal{G}_i is the union of $\tilde{\mathcal{A}}^{(i)}$ and $\{i\}$; otherwise, go to Step 4.
- 4) If $\sum_{j \in \tilde{\mathcal{A}}^{(i)}} \Omega_i^j \geq \sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - 1/(2^{C_T} - 1)$, let $x_{i,i} = 1$, and $x_{i,j} = 0, \forall j \in \tilde{\mathcal{B}}^{(i)}/\{i\}$; select the BS having the largest Ω_i^j from the set $\tilde{\mathcal{A}}^{(i)}$, set $x_{i,j} = 1$ and remove the BS from the $\tilde{\mathcal{A}}^{(i)}$ until $\sum_{j \in \tilde{\mathcal{A}}^{(i)}} \Omega_i^j < \sum_{j \in \mathcal{B}} \Omega_i^j + \tilde{\sigma}_i^2 - 1/(2^{C_T} - 1)$; allocate all BSs having $x_{i,j} = 1$ to the i -th UE as its cooperative cluster \mathcal{G}_i .
- 5) For all $j \in \mathcal{G}_i$, let $B_j = B_j + 1$; if $B_j = B_T$, delete the j -th BS from the candidate BS set for the remaining UEs in \mathcal{U} except for the j -th one.
- 6) Repeat Step 2 through 5 until all UEs in \mathcal{U} finish their clustering.

cooperative processing and therefore is negligible. With sufficient backhaul capacity, the low complexity and fast convergence properties of the clustering algorithms guarantee that it would not be difficult to keep pace with the dynamic change of the wireless channels.

V. NUMERICAL RESULTS

In this section, we validate the performance of the proposed user-centric cell clustering algorithms through numerical examples. As in [13] and [19], a 19-cell wireless network employing the urban macro cell system model was simulated to evaluate the performance of the proposed user-centric dynamic cell clustering algorithms.

As has been discussed in Section II, in the system we only considered one single sub-band, and one single UE is randomly placed within the cell range of each BS (which is the serving BS of the UE) according to uniform distribution. A total number of 10,000 independent realizations were simulated for UE locations and channel states. Assume that the receiving antennas of each BS are co-located, which implies they share the same path-loss and large-scale fading. Normalized equal transmission power is assumed for all UEs. Numerical simulation model parameters are summarized in Table 1. The uplink channel from the i -th UE to the k -th receiving

TABLE 1. System setting parameter values for numerical simulations.

Cell radius	500 m
Frequency reuse factor	1
Bandwidth	10 MHz
Number of UEs per cell	1
Number of receiving antennas per BS	2
Number of transmit antennas per UE	1
UE transmit PSD	-27 dBm/Hz
BS receiving antenna gain	11 dBi
Background noise PSD	-169 dBm/Hz
BS noise figure	7 dB

antenna at the j -th BS is modeled as

$$h_{i,j,k} = \gamma_{i,j,k} \sqrt{G\beta d_{i,j}^{-\alpha} \Gamma_{i,j}}, \tag{74}$$

where $\gamma_{i,j,k}$ denotes the small scale fading coefficient following circular symmetric complex Gaussian distribution $\gamma_{i,j,k} \sim \mathcal{NC}(0, 1)$, G is the BS receiving antenna gain, $\Gamma_{i,j}$ denotes the log-normal distributed shadowing coefficient which has a dB spread of 8dB, $d_{i,j}$ is the distance in kilometers between the i -th UE and the receiving antenna of the j -th BS, and α and β denote the path-loss exponent and the path-loss constant, respectively. The path-loss model (in dB) employed in the simulation is given by [11]

$$PL_{i,j} = 148.1 + 37.6 \log_{10}(d_{i,j}), \tag{75}$$

which corresponds to the model parameters $\alpha = 3.76$ and $\beta = 10^{-14.81}$.

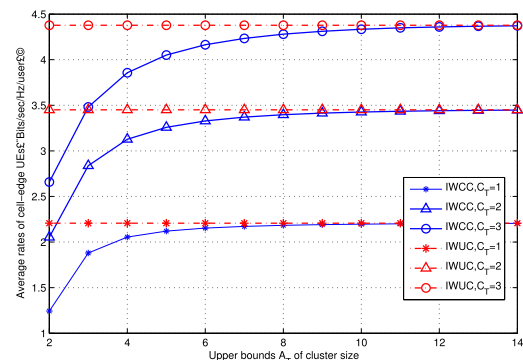


FIGURE 2. The achievable uplink rates of cell-edge UEs by clustering and cooperative processing with different A_T, C_T when $B_T = 18$.

We first studied uplink rates achieved by cell-edge UEs using the proposed IWUC and IWCC algorithms with fixed BS cooperation index B_T . Different combinations of (A_T, C_T) were used in the simulation, and the corresponding results are shown in Fig.2. In Fig.2, the performance gap between the two algorithms is greater with smaller A_T and/or greater C_T . As we increase the value of A_T , the achievable cell-edge UE rate of the IWCC algorithm approaches that of the IWUC algorithm. A smaller C_T would result in smaller number of cell-edge UEs requiring clustering and cooperative receiving for QoS provisioning, and the target of clustered transmission rates of the cell-edge UEs is lower such that

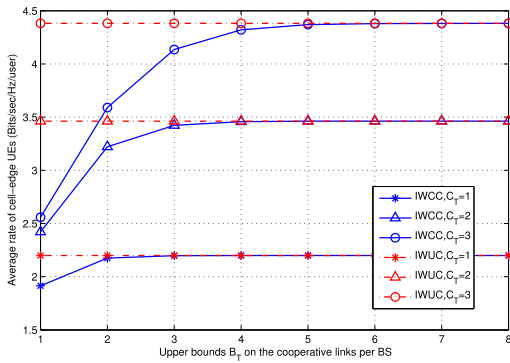


FIGURE 3. The achievable uplink rates of cell-edge UEs by clustering and cooperative processing with different B_T , C_T when $A_T = 19$.

it can be achieved using smaller cluster sizes. On the other hand, A_T reflects the amount of the cooperative resource that each UE can use for clustered cooperative receiving. Less cooperative resource can be allocated to each UE in IWCC when A_T is smaller. As a consequence, it is more difficult for the UEs to achieve higher C_T when A_T is small, which result in a wider performance gap between the IWUC and IWCC algorithms. Therefore for larger C_T , a relatively greater A_T value should be used in the IWCC algorithm to approach the performance of the IWUC case, which indicates a higher demand for cooperative processing.

By fixing $A_T = 19$, Fig.3 presents the achievable rate performance of cell-edge UEs achieved by the IWUC and IWCC algorithms, with different combinations of (B_T, C_T) . Similar to the observations from Fig.2, with greater C_T , i.e. higher QoS requirement, the IWCC tends to have higher cooperation demand, which is reflected by the BS cooperation index B_T , to approach the performance of the IWUC.

Comparisons with existing clustering schemes were also made for the proposed algorithms with cooperative resource constraint values $A_T = 4$ and $B_T = 3$, and the QoS requirement (uplink rate threshold) was set to $C_T = 2$ Bits/sec/Hz/user. The schemes used for comparison include: the static clustering algorithm with fixed cluster size of 7 (denoted as ‘Static’) [8], the interference weight based non-overlapping clustering algorithm in [13] (denoted as ‘IW’) also with fixed cluster size of 7, the channel state based user-centric clustering algorithms with the fixed cluster size 4 and 7 (denoted as ‘CS-4’ and ‘CS-7’) [19].²

Fig.4 presents the average cluster size of cell-edge UEs using different clustering algorithms. Although fixed cluster size is set in the ‘Static’ and ‘IW’ algorithms, the practical cluster size is smaller due to the limitation of a 19-cell model used in the simulation. It can be observed from Fig.4 that the proposed IWCC algorithm requires the smallest average cluster size. Compared to the IWUC algorithm, which already

²The CS algorithms from [19] were originally proposed for the downlink. Without loss of generality, they were modified in this work to adapt to the uplink system settings. The corresponding computations and performance comparisons were conducted by replacing the downlink channel strength measures by their uplink counterparts.

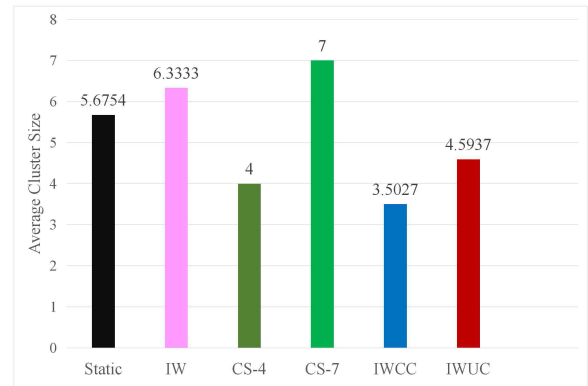


FIGURE 4. The average cluster size with different clustering strategies.

outperformed existing clustering schemes with nonconstant cluster sizes, the average cluster size of the IWCC was further reduced by 24% and achieved the smallest in the comparison. For cell-edge UEs experiencing extremely poor channel state, the IWUC algorithm allocates unconstrained cooperative resources to these UEs, which is reflected by increased average cluster size. While for the IWCC, there is a trade-off between the QoS provisioning and the A_T constraint for those extremely unfavorable cell-edge UEs.

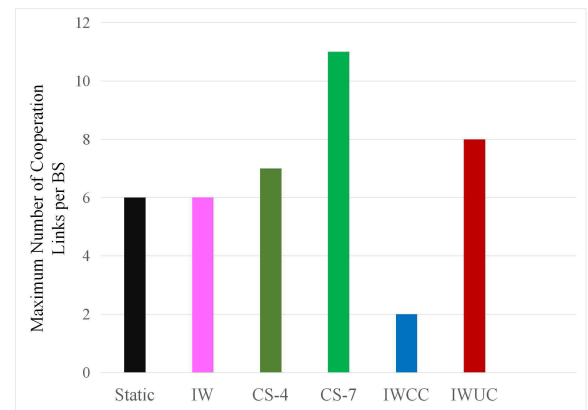


FIGURE 5. The maximum cooperation links per BS achieved by different clustering strategies.

The maximum number of cooperation links per BS achieved by different user-centric clustering algorithms are compared in Fig.5. As discussed earlier, the number of cooperation links a BS provides is a direct indicator of the cooperation burden of the BS. Note that the BS’s cooperation burden also increases dramatically with the number of sub-carriers if the scheme is deployed independently for each sub-carrier. The difference between various clustering algorithms in the single sub-carrier case (shown in Fig.5) will be further magnified when multiple sub-carriers are being scheduled. It is therefore significant to control the number of cooperation links per BS in the single sub-carrier problem under investigation. In Fig.5, all clustering algorithms exhibit considerably large maximum cooperation links per BS, except the proposed IWCC algorithm. This is because IWCC obeys

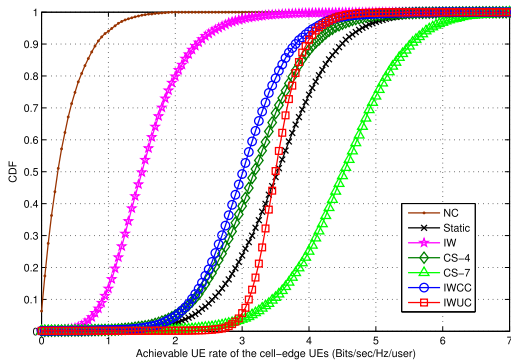


FIGURE 6. The UE rate CDFs of the cell-edge UEs achieved by different clustering strategies.

strictly the constraint on the BS cooperation index $B_T = 3$. Even compared with the CS-4 algorithm which specifies a relatively small fixed cluster size, the maximum number of cooperation links per BS of the IWCC is 60% lower, which indicates much superior control of BS cooperation burden. Compared with the worst CS-7 algorithm, near 80% of the cooperation burden reduction was achieved by the IWCC.

Fig.6 plots the cumulative distribution functions (CDFs) of the uplink rates of cell-edge UEs (those with $C_i^{(NC)} < C_T$) achieved by different clustering algorithms. The performance of the non-cooperation case is also shown as a lower bound benchmark (denoted as ‘NC’). Among all the clustering algorithms, the IW algorithm exhibits the worst performance in terms of UE rate CDF. This is because the IW strategy divides all the cells in the network into non-overlapping clusters, where each cluster conducts cooperative receiving for all the cell-edge UEs within its range. Degradation of the rate performance is thus introduced by the resource sharing mechanism. The CS-7 achieved the most superior rate CDF in Fig.6, which is the outcome of using much larger cluster size, i.e. much higher system overhead, than the other schemes. From the resource-performance trade-off point of view, the CS-7 algorithm gives an upper bound benchmark for the rate CDF and cooperation resource consumption. Although the IWUC algorithm can obtain an approximate optimal solution to the clustering problem $P1$ without introducing per-UE or per-BS resource constraint, its UE rate performance in Fig.6 is not optimal because the optimization object of $P1$ is minimization of the cluster size. Specifically, the cluster size would stop growing once the cooperative rate of the UE reaches the rate threshold. By further restricting the available cooperation resources, the rate performance of the IWCC algorithm is further degraded, as shown in Fig.6.

Fig.7 further presents the achievable UE rate CDFs of all the UEs, where both cell-edge and cell-centre UEs are taken into account. To avoid unnecessary cooperation, clustering and cooperative receiving are only conducted for cell-edge UEs who do not satisfy the rate threshold C_T with single cell processing, while QoS provisioning can be guaranteed for the cell-centre UEs without multi-cell joint processing.

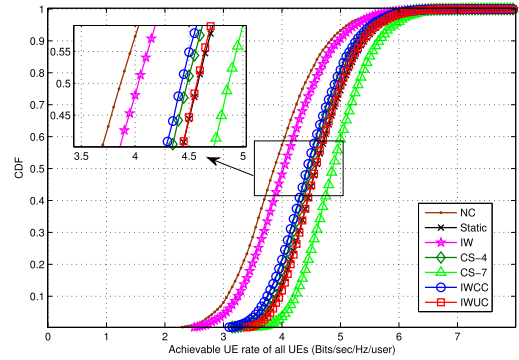


FIGURE 7. The UE rate CDFs of all UEs achieved by different clustering strategies.

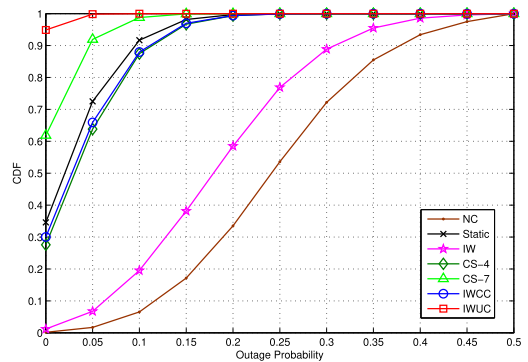


FIGURE 8. The CDF of the outage probability of all UEs in the network achieved by different clustering strategies.

Compared with Fig.6, Fig.7 shows similar trends but narrower gaps among the CDF curves.

Fig.8 shows the CDF of the QoS outage probabilities of all UEs in the network, where the QoS (rate) threshold is set to $C_T = 2$ Bits/sec/Hz/user. The outage event occurs when the UE rate falls below the outage rate threshold, and it is the main consideration of QoS provisioning. Without imposing further constraints, the proposed IWUC algorithm focuses on the satisfaction of the rate threshold with a minimum cluster size, which leads to the best performance on the outage analysis in Fig.8. The CS-7 algorithm, even though consumes the highest cooperative resources, achieved worse outage probability performance than the IWUC in Fig.8. This is because fixing the cluster size in CS-7 would waste some BS cooperation resources on UEs with relatively good channel condition so that the UEs experiencing even worse channel condition may not receive sufficient cooperation resources. Compared with the CS-4 scheme, the proposed IWCC algorithm exhibits significantly lower resource demand according to results shown in Figs.4 and 6. But in terms of outage performance shown in Fig.8, the IWCC algorithm slightly outperforms the CS-4, which indicates a more efficient cooperation resource utilization of the proposed clustering mechanism.

To further evaluate trade-off in clustered cooperative receiving, we studied average cooperative rate gain (with respect to NC) achieved by unit cooperation resource,

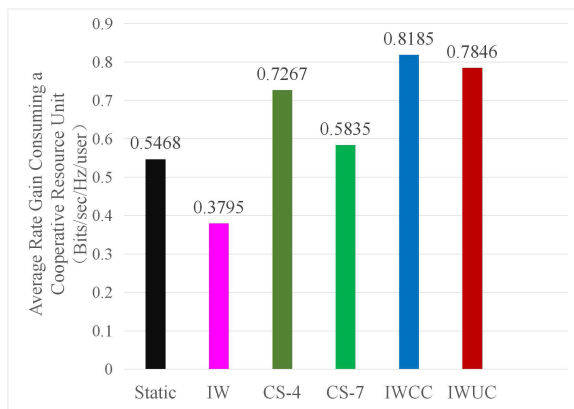


FIGURE 9. The average rate gain consuming a cooperative resource unit with different clustering algorithms.

i.e. one cooperation link occupying the backhaul on one time-frequency resource block. The corresponding results are shown in Fig.9. It is observed that the proposed IWCC and IWUC algorithms perform much better than the other algorithms in comparison. Particularly the IWCC algorithm utilized the cooperation resources most efficiently, which verifies the conclusion we made above. By putting constraints to upper bound the cluster size and per-BS cooperation resource, the IWCC scheme imposed stringent control over the cooperation resources such that efficient utilization of the resources can be achieved. The IWUC algorithm, even though outperforms the IWCC on both rate and outage performance, consumed significantly higher cooperation resources, which led to less efficient use of cooperation resources compared with the IWCC scheme. With similar cooperation resource consumption, the CS-4 algorithm achieved lower rate gain per unit cooperation resource (0.7267 v.s. 0.8185), compared with the IWCC scheme.

TABLE 2. Computational complexity of different clustering schemes.

Clustering Scheme	IW	CS	IWUC	IWCC
Times of Additions (Percentage)	1946 (220%)	885 (100%)	4145 (468%)	1015 (115%)
Times of Multiplications (Percentage)	2105 (216%)	975 (100%)	2177 (223%)	1001 (103%)

Table 2 summarizes computational complexities of different clustering algorithms, where the number of both additions and multiplications are taken into account. The static algorithm is out of consideration, since it exhibits the ignorable computational complexity due to the nature of static strategy. The CS-4 and CS-7 algorithms have the same computational complexity in clustering, because the criteria for cooperative partner selection are the same. The only difference lies in the number of cooperative partners, which is labeled as ‘CS’ in Table 2. It is straightforward that the computational complexity of the IWUC scheme is much higher than that of CS and IWCC, which is due to the iterative search of the Lagrangian multiplier. The IW algorithm designs non-overlapping clusters for all cell-edge UEs at the same

time, which leads to a large dimensionality of the clustering optimization problem. Hence, the computational complexity of IW is also much higher than that of CS and IWCC, but is slightly lower than that of IWUC. The computational complexity of the proposed IWCC algorithm is close to that of the least complex CS algorithm, where the numbers of additions and multiplications are 15% and 3% higher than CS, respectively. By imposing critical constraints on the cluster size and the BS cooperation resources, the IWCC algorithm achieved a 12.6% improvement on the rate gain compared with the CS-4 scheme with the same cost of cooperation resources, while exhibiting similar cell-edge rate and outage performance. Therefore, the proposed IWCC algorithm achieved a satisfactory trade-off between performance and computational complexity.

VI. CONCLUSION

In this paper, we have investigated dynamic user-centric clustering for uplink cooperative receiving in multi-cell wireless networks subject to constraints on BS cooperation resources. The focus of the study has been placed on cell-edge UEs, which are defined by achievable uplink rates when cooperation is not available. A resource efficient cluster size minimization problem has been formulated to achieve improved QoS provisioning for cell-edge UEs through cooperative processing of clustered BSs. The 0-1 integer programming problem that minimizes the user-centric cluster size has been solved by an IWUC algorithm, which depends on the inter-cluster interference weight (IW) and solved the problem by dual decomposition and subgradient-based technique. By imposing constraints on the cluster size of each cell-edge UE and on cooperation burden of each BS, an IWCC algorithm has been proposed to address the further constrained clustering problem with greedy heuristics. Numerical results have shown that the proposed IWUC algorithm significantly outperforms other clustering algorithms in outage probability, which indicates superior QoS provisioning property. The IWCC algorithm, on the other hand, has achieved good tradeoff between the gain and cost due to clustering and cooperative processing, with modest computational complexity. Specifically, it has exhibited the highest rate gain per unit cooperation resource consumption and has demonstrated good control over the cooperation burden of the BSs and the system.

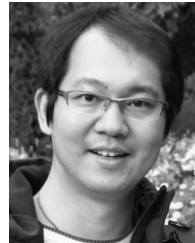
REFERENCES

- [1] D. Gesbert, S. Hanly, H. Huang, S. Shamai (Shitz), O. Simeone, and W. Yu, “Multi-cell MIMO cooperative networks: A new look at interference,” *IEEE J. Sel. Areas Commun.*, vol. 28, no. 9, pp. 1380–1408, Dec. 2011.
- [2] R. Irmer *et al.*, “Coordinated multipoint: Concepts, performance, and field trial results,” *IEEE Commun. Mag.*, vol. 49, no. 2, pp. 102–111, Feb. 2011.
- [3] R. Zhang *et al.*, “Advances in base- and mobile-station aided cooperative wireless communications: An overview,” *IEEE Veh. Technol. Mag.*, vol. 8, no. 1, pp. 57–69, Mar. 2013.
- [4] P. Marsch and G. Fettweis, “On uplink network MIMO under a constrained backhaul and imperfect channel knowledge,” in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2009, pp. 1–6.

- [5] S. Jain, S.-J. Kim, and G. B. Giannakis, "Backhaul-constrained multicell cooperation leveraging sparsity and spectral clustering," *IEEE Trans. Wireless Commun.*, vol. 15, no. 2, pp. 899–912, Feb. 2016.
- [6] Z. Hasan, H. Boostanimehr, and V. K. Bhargava, "Green cellular networks: A survey, some research issues and challenges," *IEEE Commun. Surveys Tuts.*, vol. 13, no. 4, pp. 524–540, 4th Quart., 2011.
- [7] N. Wang, E. Hossain, and V. K. Bhargava, "Backhauling 5G small cells: A radio resource management perspective," *IEEE Wireless Commun.*, vol. 22, no. 5, pp. 41–49, Oct. 2015.
- [8] S. Venkatesan, "Coordinating base stations for greater uplink spectral efficiency in a cellular network," in *Proc. IEEE Int. Symp. Pers. Indoor Mobile Radio Commun. (PIMRC)*, Sep. 2007, pp. 1–5.
- [9] J. Zhang, R. Chen, J. G. Andrews, A. Ghosh, and R. W. Heath, "Networked MIMO with clustered linear precoding," *IEEE Trans. Wireless Commun.*, vol. 8, no. 4, pp. 1910–1921, Apr. 2009.
- [10] P. Marsch and G. Fettweis, "A framework for optimizing the uplink performance of distributed antenna systems under a constrained backhaul," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2007, pp. 975–979.
- [11] A. Papadogiannis, D. Gesbert, and E. Hardouin, "A dynamic clustering approach in wireless networks with multi-cell cooperative processing," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2008, pp. 4033–4037.
- [12] A. Papadogiannis and G. C. Alexandropoulos, "The value of dynamic clustering of base stations for future wireless networks," in *Proc. IEEE Int. Conf. Fuzzy Syst. (FUZZ)*, Jul. 2010, pp. 1–6.
- [13] M. Yoon, M.-S. Kim, and C. Lee, "A dynamic cell clustering algorithm for maximization of coordination gain in uplink coordinated system," *IEEE Trans. Veh. Technol.*, vol. 65, no. 3, pp. 1752–1760, Mar. 2016.
- [14] D. Liu, S. Han, C. Yang, and Q. Zhang, "Semi-dynamic user-specific clustering for downlink cloud radio access network," *IEEE Trans. Veh. Technol.*, vol. 65, no. 4, pp. 2063–2077, Apr. 2016.
- [15] P. Marsch and G. Fettweis, "Static clustering for cooperative multi-point (CoMP) in mobile communications," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2011, pp. 1–6.
- [16] J. Zhao, T. Zhang, Z. Zeng, Q. Gao, and S. Sun, "An overlapped clustering scheme of coordinated multi-point transmission for LTE-A systems," in *Proc. IEEE 14th Int. Conf. Commun. Technol. (ICCT)*, Nov. 2012, pp. 479–484.
- [17] V. Garcia, Y. Zhou, and J. Shi, "Coordinated multipoint transmission in dense cellular networks with user-centric adaptive clustering," *IEEE Trans. Wireless Commun.*, vol. 13, no. 8, pp. 4297–4308, Aug. 2014.
- [18] S. Bassoy, M. Jaber, M. A. Imran, and P. Xiao, "Load aware self-organising user-centric dynamic CoMP clustering for 5G networks," *IEEE Access*, vol. 4, pp. 2895–2906, 2016.
- [19] J. Zhao and Z. Lei, "Clustering methods for base station cooperation," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Apr. 2012, pp. 1–6.
- [20] D. Zennaro, S. Tomasin, and L. Vangelista, "Base station selection in uplink macro diversity cellular systems with hybrid ARQ," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 6, pp. 1249–1259, Jun. 2011.
- [21] K. Balachandran, J. H. Kang, K. Karakayali, and K. M. Rege, "NICE: A network interference cancellation engine for opportunistic uplink cooperation in wireless networks," *IEEE Trans. Wireless Commun.*, vol. 10, no. 2, pp. 540–549, Feb. 2011.
- [22] P. Marsch and G. Fettweis, "Uplink CoMP under a constrained backhaul and imperfect channel knowledge," *IEEE Trans. Wireless Commun.*, vol. 10, no. 6, pp. 1730–1742, Jun. 2011.
- [23] N. Wang, E. Hossain, and V. K. Bhargava, "Joint downlink cell association and bandwidth allocation for wireless backhauling in two-tier HetNets with large-scale antenna arrays," *IEEE Trans. Wireless Commun.*, vol. 15, no. 5, pp. 3251–3268, May 2016.
- [24] M. L. Fisher, "The Lagrangian relaxation method for solving integer programming problems," *Manage. Sci.*, vol. 50, no. 12, pp. 1861–1871, 2004.



ZHE ZHANG received the B.E. degree in electronic and information engineering from The First Aviation Academy of Chinese Air Force, Xinyang, China, in 2009, and the Ph.D. degree in information and communication engineering from Zhengzhou University, Zhengzhou, in 2017. She is currently a Lecturer with the School of Computer and Communication Engineering, Zhengzhou University of Light Industry, Zhengzhou. Her research interests include radio resource management, heterogeneous networks, and cooperative communications.



NING WANG (S'09–M'13) received the B.E. degree in communication engineering from Tianjin University, China, the M.A.Sc. degree in electrical engineering from The University of British Columbia, Canada, and the Ph.D. degree in electrical engineering from the University of Victoria, Canada, in 2004, 2010, and 2013, respectively. From 2004 to 2008, he was with the China Information Technology Design and Consulting Institute as a Mobile Communication System Engineer, specializing in planning and design of large-scale commercial mobile communication networks, network traffic analysis, and radio network optimization. He was a Post-Doctoral Research Fellow with the Department of Electrical and Computer Engineering, The University of British Columbia, from 2013 to 2015. Since 2015, he has been with the School of Information Engineering, Zhengzhou University, Zhengzhou, China, where he is currently an Associate Professor. He also holds adjunct appointment with the Department of Electrical and Computer Engineering, McMaster University, Hamilton, Canada. His research interests include resource allocation and security designs of future cellular networks, channel modeling for wireless communications, statistical signal processing, and cooperative wireless communications.



JIANKANG ZHANG (S'08–M'12) received the B.Sc. degree in mathematics and applied mathematics from the Beijing University of Posts and Telecommunications in 2006, and the Ph.D. degree in communication and information systems from Zhengzhou University in 2012. From 2009 to 2011, he was a Visiting Researcher in electronics and computer science with the University of Southampton, U.K. Since 2012, he has been a Lecturer with the School of Information Engineering, Zhengzhou University. From 2013 to 2014, he was a Post-Doctoral Researcher with McGill University, Canada. Since 2014, he has been a Research Fellow with the University of Southampton, U.K. His research interests are in the areas of wireless communications and signal processing, aircraft communication, and wireline communication.



XIAOMIN MU received the B.E. degree from the Beijing Institute of Technology, Beijing, China, in 1982. She is currently a Full Professor with the School of Information Engineering, Zhengzhou University, Zhengzhou. She has co-authored many research papers in the field of communications and signal processing. She is also a co-author of two textbooks. Her research interests include signal processing in communication systems, wireless communications, and cognitive radio networks.

...