Joint Communication and Computing Resource Allocation in 5G Cloud Radio Access Networks

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***Abstract*—Cloud-radio access network (C-RAN) is regarded as a promising solution to manage heterogeneity and scalability of future wireless networks. The centralized cooperative resource allocation and interference cancellation methods in C-RAN significantly reduce the interference levels to provide high data rates. However, the centralized solution is not scalable due to the dense deployment of small cells with fractional frequency reuse, causing severe inter-tier and inter-cell interference turning the resource allocation and user association into a more challenging problem. In this paper, we investigate joint communication and computing resource allocation along with user association, and baseband unit (BBU) and remote radio head (RRH) mapping in C-RANs. We initially establish a queueing model in C-RAN, followed by formulation of two optimization problems for communication [e.g., resource blocks (RBs) and power] and computing [e.g., virtual machines (VMs)] resources allocation with the aim to minimize mean response time. User association along with the RB allocation, interference, and queueing stability constraints are considered in the communication resource optimization problem. The computing resource optimization problem considers BBU-RRH mapping and VM allocation for small cells, constrained to BBU server capacity and queueing stability. To solve the communication and computing resource optimization problem, we propose a joint resource allocation solution that considers a double-sided auction based distributed resource allocation (DS-ADRA) method, where small cell base stations and users jointly participate using the concept of auction theory. The proposed method is evaluated via simulations by considering the effect of bandwidth utilization percentage, signal-to-interference ratio threshold value and the number of users. The results show that the proposed method can be successfully implemented for 5G C-RANs.**

***Index Terms*—Distributed resource allocation, user association, BBU-RRH mapping, VM Allocation, C-RAN, Auction Theory.**

I. Introduction

THE ever-growing use of smart phones and portable devices such as tablets and smart watches increases the growth of cellular Internet data traffic exponentially. According to the Cisco visual networking report, the global mobile data traffic will show 53 percent compound annual growth rate from 2015 to 2020, where 75 percent of data will be video, producing 30.6 exabytes per month by 2020 [1]. It is anticipated that within the next five years, 11.6 billion connected devices including IoT devices will increase network connection speeds by more than threefold, and the number of mobile-connected devices per capita will reach 1.5 by 2020 [1], [2].

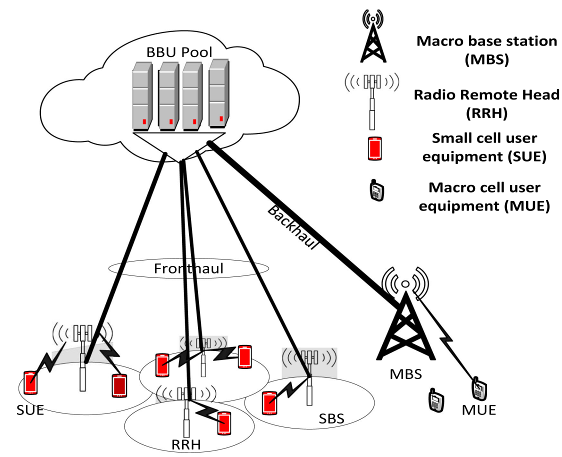

Fig. 1. Small cell-based C-RAN architecture for 5G networks.

To deal with ever-increasing demand of user association and resource allocation in cellular networks, the architecture of cloud radio access networks (C-RANs) is envisioned as an attractive paradigm that takes advantage of managing large number of small cells through the centralized cloud controller, known as baseband processing unit or baseband unit (BBU) pool. Fig. 1 depicts a small cell-based C-RAN architecture, where small cell base stations, which are regarded as radio remote heads (RRHs), are responsible for RF signal transmission to/from users in the small cell and to/from BBU pool through fronthaul links. The access requests of users are transmitted from RRH to BBU pool for baseband processing. To satisfy the demand for large bandwidth and data rate, the optical fiber is generally considered as an ideal fronthaul link for C-RAN, whereas wired and wireless links support C-RAN backhaul [2]. The inspiring factor for such a centralized structure of C-RAN is to minimize capital expenditure (CAPEX) and operating expenditure (OPEX) costs as well as to support scalability and flexibility in deployment of RRHs [3]. However, user association, cell activation, dynamic resource allocation based on users' QoS requirements, workload scheduling in BBU pool, BBU-RRH mapping, etc. are the major challenging issues in C-RANs.

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A. Related Works

The computing resource optimization problem becomes a challenging task in cloud environment in terms of utilizing minimum physical resources (e.g, VMs, CPUs, servers), optimizing resource costs and minimizing delay. Moreover, joint optimization of computation and communication resource allocation is considered in mobile cloud computing (MCC) [16] and mobile edge computing (MEC) [4]–[6] environments. In [16], the authors optimized multi-task offloading decision with the help of computing access point in the MCC environment. Similarly, co-operation of users is considered in [4] to optimize energy consumption in computing and communication resource allocation in MEC. Computation offloading and fairness based MEC server selection in terms of cost minimization is considered in [5]. Similarly, in C-RANs and heterogeneous C-RANs (H-CRANs), the BBU server selection in a BBU pool and RRH-BBU mapping are considered as computing resource allocation. On the other hand, in C-RANs and H-CRANs, the computing and communication resource optimization problems consider delay, costs, RRH/VM utilization ratio, fairness, throughput, spectrum and energy efficiency as QoS/QoE parameters [8]–[10], [17].

In C-RANs and H-CRANs, the data rate provisioning can be significantly improved by the fractional frequency reuse performed by small cells [18], in which specific partitions of the spectrum are shared between RRHs and the MBS to alleviate the inter-tier interference. In [19], authors studied a combinatorial optimization problem for joint resource block (RB) and power allocation in an OFDM based C-RAN system, in which the inter-tier interference is cancelled by imposing a constraint at the RRH side. Moreover, the central cooperative interference cancellation in C-RANs can significantly reduce the interference levels to provide high data rates. However, the centralized method is not scalable due to the dense deployment of small cells in a multi-tier system, turning the user association into a more challenging problem. Recently, the application of auction theory to allocate resources in a distributed way has received increasing attention amongst researchers exploring future wireless networks [20]–[23]. A comprehensive introduction and applicability of auction theory in wireless networks are provided in [20], [21]. Authors in [22], [24] proposed distributed framework for resource allocation in a multi-tier device-to-device communication enabled network, where they used auction theory for distributed resource allocation in [22]. In [23], authors proposed a combinational auction algorithm to address the user association problem in 60 GHz millimeter wave wireless access networks. Further studies related to C-RAN and utilizing auction theory are given in Table I, where the research problem, objective, solution approach and the solution type are given.

B. Contributions

Different from the above works, in this paper, we apply the auction theory to solve communication and computing resource allocation along with the user association and BBU-RRH mapping problem in OFDM based C-RANs with the objective to minimize delay. To the best of our knowledge, this is the first paper to consider joint communication and computing resource optimization utilizing auction theory in C-RANs, whereas in our previous work [25], we considered only communication resource allocation in C-RANs.

The main contributions of this paper can be summarized as follows:

- We establish a queueing model in C-RAN. There are two queues: i) RRH transmission and ii) baseband processing queues are considered at the radio access and BBU pool side, respectively. We formulate two optimization problems with the objective to minimize delay for small cell users.
- In the first optimization problem, we consider joint user association and communication resources (e.g., RB and power) allocation with the aim to minimize mean response time in RRH transmission queue. Maximum power, RB allocation, interference and queueing stability constraints are considered in this optimization problem.
- In the second optimization problem, we consider VM allocation to each small cell, constrained to one-to-one mapping with BBU and RRH, with maximum capacity limit of each BBU, and queueing stability constraint in baseband processing queue.
- To solve the communication and computing resource allocation problems jointly, we propose a double-sided distributed resource allocation method using auction theory, addressing all the aforementioned constraints. In the proposed method, the small cell users and base stations cooperatively decide transmission alignment (e.g., RB and power) and service rate. Using the communication resource allocation information for RBs and power, the centralized cloud controller, referred to as the auctioneer in this paper, decides the computing resource for each RRH using the concept of probability theory.
- The effectiveness of the proposed method is verified through Monte Carlo simulations.

The rest of the paper is organized as follows. In Section II, the system model for communication and computing resource allocation in C-RAN is described. The corresponding optimization problem and the analytical solution for optimal power allocation are provided in Sections III and IV, respectively. Section V presents the solution method of auction-based distributed resource allocation. Section VI provides the numerical results of the proposed method. Finally, Section VII concludes the paper.

II. System Model and Assumptions

In this section, we initially present a queueing model for the C-RAN in the network model subsection. Then, the system models of RRH transmission and baseband processing queues are described in the subsequent subsections, respectively.

A. Network Model

In this paper, we consider an OFDM based two tier uplink C-RAN where $\mathcal{N}$ number of RRHs are covered by one macro cell in an underlay manner. Each small cell user (SUE) is equipped with one antenna and each RRH has L antennas. The system supports $\mathcal{K}$ number of users, where SUE is indexed by

TABLE I
SUMMARY OF WORKS ON RESOURCE OPTIMIZATION PROBLEMS

Ref.	Research Problem	Objectives	Solution Approach	Solution Type
Works on MEC				
[4]	-Computation and communication resource allocation	-Minimize the energy consumption	-Lagrange dual method	Centralized
[5]	-Computation and communication resource allocation, -MEC sever selection	-Minimize cost	-Hungarian and fairness based algorithm	N/A†
[6]	-Spectrum allocation -Computation offloading -Content caching	-Maximize revenue	-Augmented Lagrangian based alternating direction method	Distributed
Works on C-RAN				
[7]	-User association	-Maximize ergodic capacity	-Received power based approach: i) N-best, ii) N^{th} best, and iii) single best	Centralized
[8]	-Computing resource allocation	-Energy efficiency	-Apply queueing model at remote radio head (RRH) side -Apply convex solver and WMSE approach	Distributed
[9]	-User association, -Communication resource allocation -Congestion control	-Energy efficiency, -Minimize delay	-Apply queueing theory -Stochastic geometric theory	N/A†
[10]	-BBU-RRH mapping -Communication resource allocation	-Minimize fronthaul overhead	-Heuristic algorithm	N/A†
[11]	-Communication resource allocation -Admission control	-Maximize the tolerable interference level	-Low complexity algorithm, -Lagrange multiplier	N/A†
Work utilizing auction theory				
[12]	-RB allocation	-Maximize throughput	-First price seal-bid based SINR auction method	Distributed
[13]	-Computing resource allocation	-Maximize utility	-Two Tier auction method	Distributed
[14]	-Computing resource allocation	-Maximize utility	-Combinational double auction method	Centralized
[15]	-Spectrum allocation	-Maximize revenue	-Time-line based auction method	Distributed
Proposed scheme	-User association, -Communication resource allocation -Computing resource allocation	-Minimize delay	-Lagrange multiplier -Double sided auction method -Probabilistic method for BBU-RRH maping	Distributed

† No information is available

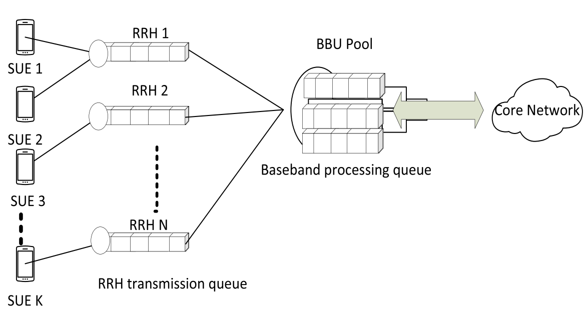

Fig. 2. Queueing model of two tier C-RAN.

$j = \{1, 2, 3, ..., \mathcal{K}\}$ and RRH is indexed by $i = \{1, 2, 3, ..., \mathcal{N}\}$. For simplicity, we assume that each user is associated with one of the RRHs and one resource block is assigned between the user and the RRH. The system supports $\mathcal{R}$ number of resource blocks, indexed by $r = \{1, 2, 3, ..., \mathcal{R}\}$. Fig. 2 represents the queueing network model of the two-tier C-RAN network. Each RRH has a transmission queue which receives requests from small cell users and processes the request at a pre-defined service rate. The RRH transmits the access requests of users to the BBU pool for baseband processing. The BBU pool is maintained by software defined C-RAN controller or scheduler which distributes the incoming requests to BBU servers for computation. Similar to [26], we assume that each BBU server runs a limited number of VMs, which is bounded by the maximum capacity of each BBU server. For a summary of symbols and parameters, a list is provided in Table II.

B. RRH Transmission Queue

Fig. 3 represents a queueing model for RRH. In the OFDM based C-RAN, RRHs receive requests in transmission time interval (TTI). At a given TTI, the RRH receives requests from $\mathcal{K}$ number of SUEs with Poisson arrival rate $\lambda_1^{SUE}, \lambda_2^{SUE}, ..., \lambda_{\mathcal{K}}^{SUE}$. The average incoming requests at i^{th} RRH is represented as $\lambda_i^{RRH} = \sum_{j=1}^{\mathcal{K}} a_{i,j}\lambda_j^{SUE}$, where $a_{i,j}$ denotes the user association parameter, defined as

$$a_{i,j} = \begin{cases} 1, & \text{if user } j \text{ is associated with } i^{\text{th}} \text{ RRH}, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

TABLE II
LIST OF SYMBOLS

	Symbol	Description
Set	$\mathcal{N}$	Total number of RRHs
	$\mathcal{K}$	Total number of SUEs
	$\mathcal{R}$	Total number of RBs
	M	Total number of BBUs
	U	Maximum capacity of each BBU
Index	i	Indexing for RRH
	j	Indexing for SUE
	r	Indexing for RB
	m	Indexing for BBU
Queueing Parameters	λ_i^{RRH}	Average incoming requests of the i^{th} RRH, also denotes average data rate requirements of the i^{th} RRH
	λ_m^{BBU}	Average incoming requests of the m^{th} BBU
	$\mu_{i,j}$	Service rate of the i^{th} RRH for the j^{th} SUE
	μ_i^{RRH}	Mean service rate of i^{th} RRH
	μ_m^{BBU}	Mean service rate of m^{th} BBU
	T_i^{RRH}	Average response time of i^{th} RRH
	T_m^{BBU}	Average response time of m^{th} BBU
Optimization Parameters	$a_{i,j}$	User association parameter of i^{th} RRH for j^{th} SUE
	$b_{i,m}$	BBU-RRH mapping parameter of i^{th} RRH for m^{th} BBU
	$\beta_{i,j}^r$	RB allocation r^{th} RB to i^{th} RRH for user j
	$P_{i,j}^r$	Power allocation from i^{th} RRH to user j on r^{th} RB
Channel Parameters	$h_{i,j}^r$	The channel gain from i^{th} RRH to j^{th} SUE on r^{th} RB
	P_i^{max}	Maximum power of RRH i
	$\gamma_{i,j}^r$	SINR of j^{th} SUE conneted to i^{th} RRH on r^{th} RB
	γ^{th}	SINR threshold value
Others	$\Gamma_{i,j}^r$	Parameter for both user association and RB allocation.
	$\mathcal{A}_{i,j}^r$	Parameter for power allocation
	$\sigma, \varsigma, \upsilon$ ϕ, φ, ψ	Lagrange multiplier vector
Auction Parameters	F_j^1,F_j^2	Bid information generated by user j
	F_i^1, F_i^2	Bid information for RRH i, generated by auctioneer
	F_i^3	Bid information generated by RRH i
	F_j^3	Acknowledgement from user j
	F_i^3	Acknowledgement from RRH i
	$\mathcal{B}_i$	Benefit of RRH i
	$\mathcal{U}_{ij}$	Utility of user j associated with RRH i

The arrival of scheduled requests to i^{th} RRH follows Poisson process with an average of λ_i^{RRH} and the inter-arrival service time is exponentially distributed with rate μ_i^{RRH}. The service rate of each RRH is related with transmission rate that varies with time variation of channel and states of the base station [27], [28]. The service process of each RRH follows an M/M/1 queuing model. The average response time of i^{th} RRH can be formulated as:

$$T_i^{RRH} = \frac{1}{\mu_i^{RRH} - \lambda_i^{RRH}}. \tag{2}$$

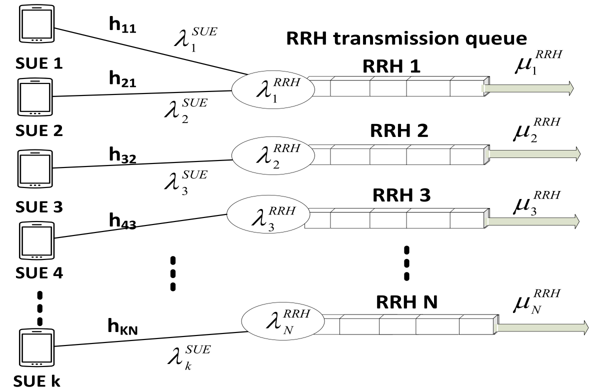

Fig. 3. RRH transmission queue.

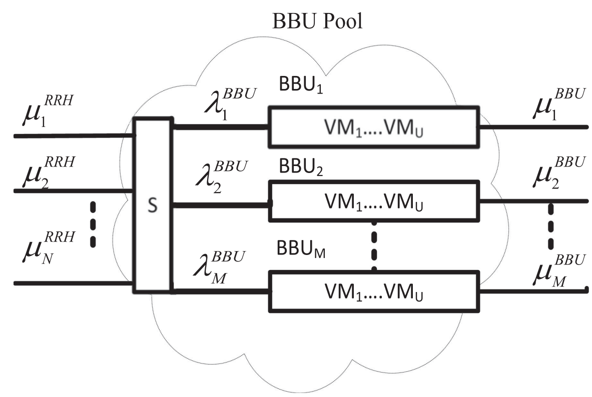

Fig. 4. Baseband processing queue.

C. Baseband Processing Queue

Fig. 4 represents a queueing model for the BBU pool. In C-RAN architecture the BBU pool is considered as a master base station which runs the baseband processing function into VMs in BBU servers. Assume that the BBU pool maintains M BBU servers and each server has maximum capacity U. That means each BBU server can generate a maximum number of U VMs. For BBU-RRH mapping, we assume that all the requests from one RRH is served by one VM in one BBU server. Assume that the BBU pool receives requests in TTI. At a given TTI, each BBU server receives requests from $\mathcal{N}$ number of RRHs with exponential service rate $\mu_1^{RRH}, \mu_2^{RRH}, ..., \mu_{\mathcal{N}}^{RRH}$. The average incoming request at m^{th} BBU is represented as $\lambda_m^{BBU} = \sum_{i=1}^{\mathcal{N}} b_{i,m}\mu_i^{RRH}$, where $b_{i,m}$ denotes the BBU-RRH association parameter, defined as

$$b_{i,m} = \begin{cases} 1, & \text{if BBU } m \text{ is associated with } i^{\text{th}} \text{ RRH,} \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

The arrival of scheduled requests to m^{th} BBU follows Poisson process with an average of λ_m^{BBU} and the inter-arrival service time is exponentially distributed with rate μ_m^{BBU}. The service rate of each BBU is related with transmission rate that varies with time variation of the channel and states of the base station. The service process of each BBU follows an M/M/1 queuing model.

The average response time of m^{th} BBU can be formulated as:

$$T_m^{BBU} = \frac{1}{\mu_m^{BBU} - \lambda_m^{BBU}}. \tag{4}$$

III. Problem Formulation

Let $\beta_{i,j}^r$ be the binary variable for RB allocation defined as follows:

$$\beta_{i,j}^r = \begin{cases} 1, & \text{if RB } r \text{ is assigned to RRH } i \text{ on SUE } j, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

The channel gain from RRH i to SUE j on RB r is denoted as $h_{i,j}^r \in \mathcal{C}^{L\times 1}$. The power allocation from RRH i to user j on RB r is denoted as $P_{i,j}^r \in [0, P_i^{max}]$, where P_i^{max} is the maximum power of RRH i. The SINR achieved by SUE j connected to RRH i on RB r can be written as:

$$\gamma_{i,j}^r = \frac{|h_{i,j}^r| P_{i,j}^r}{\sum_{u\neq i, v\neq j} |h_{u,v}^r| P_{u,v}^r + \eta_0}, \tag{6}$$

where η_0 represents the zero mean and unit variance additive white Gaussian noise (AWGN) power. According to the Shannon's formula, the service rate for each user that is associated with i^{th} RRH can be obtained as:

$$\mu_{i,j} = \Delta B \sum_{r=1}^{\mathcal{R}} a_{i,j} \beta_{i,j}^r \log_2(1 + \gamma_{i,j}^r), \tag{7}$$

where ΔB represents the available bandwidth of each RB. The average service rate of RRH i can be represented by:

$$\mu_i^{RRH} = \sum_{j=1}^{\mathcal{K}} \mu_{i,j} = \Delta B \sum_{j=1}^{\mathcal{K}} \sum_{r=1}^{\mathcal{R}} a_{i,j} \beta_{i,j}^r \log_2(1 + \gamma_{i,j}^r). \tag{8}$$

All the RRHs forward the requests to the centralized BBU pool for baseband processing. In an ideal scenario, each BBU data transmission should be equivalent to the RRH data transmission rate to satisfy SUE data rate requirements [9]. Therefore, the relation between the data rate requirements of SUE and the average BBU data transmission rate can be represented by

$$\mu_m^{BBU} = \lambda_m^{BBU} = \mu_i^{RRH}. \tag{9}$$

A. Objective Function

Our objective for resource allocation is to minimize the delay of C-RAN by optimizing the average response time of each RRH and BBU server. The response time of each RRH depends on user association, RB and power allocation, and the response time of each BBU depends on BBU-RRH mapping and maximum capacity constraints. Theoretically, the delay of each RRH will be minimum when the RRH serves at the maximum rate. Therefore, the objective of each RRH can be defined as

$$\text{Minimize } T_i^{RRH} \quad \text{OR} \quad \text{Maximize } \mu_i^{RRH}. \tag{10}$$

Similarly the objective of each BBU can be defined as

$$\text{Minimize } T_m^{BBU}. \tag{11}$$

B. Constraint Sets of Communication Resource Allocation

In order to ensure the minimum delay while all users are associated with RRH and received RB to transmit data without causing interference to each other, we define the following constraint sets.

- The constraint (12) ensures that each user is associated with only one RRH, i.e.,

$$\sum_{i=1}^{\mathcal{N}} a_{i,j} = 1, \quad \forall j \in \mathcal{K}. \tag{12}$$

- The following constraint ensures that each associated user can use at most one RB for communication. For simplicity, we assume that each user and RRH connection utilizes one RB for data transmission as

$$\sum_{r=1}^{\mathcal{R}} a_{i,j} \beta_{i,j}^r \leq 1, \quad \forall i, j. \tag{13}$$

- Constraint (14) verifies the SINR threshold value for allocated RBs. For spectrum efficiency, we consider that each SUE utilizes the macro cell users' RBs only when their instantaneous SINR exceeds a threshold value

$$a_{i,j} \beta_{i,j}^r \gamma_{i,j}^r > \gamma^{th}. \tag{14}$$

- The constraint (15) ensures that each RRH selects separate RBs for users to avoid co-tier interference. In (15), S_i represents the set of users that are associated with RRH i. According to this constraint, users in S_i utilize different RBs for data transmission as

$$a_{u,i} \beta_{u,i}^r + a_{v,i} \beta_{v,i}^r \leq 1, \quad \forall r \in \mathcal{R}, \ \forall (u,v) \in S_i. \tag{15}$$

- The constraint (16) verifies the maximum power budget of each RRH and is given as

$$\sum_{j=1}^{\mathcal{K}} \sum_{r=1}^{\mathcal{R}} a_{i,j} \beta_{i,j}^r P_{i,j}^r \leq P_i^{max}, \quad \forall i \in \mathcal{N}. \tag{16}$$

- The constraint (17) maintains the queueing stability at each RRH, i.e., the arrival rate should not be greater than the service rate, which is

$$\lambda_i^{RRH} \leq \mu_i^{RRH}, \quad \forall i \in \mathcal{N}. \tag{17}$$

Considering the objective of each RRH and the aforementioned constraints, the resource optimization problem for each RRH can be formulated as:

$$(\mathbf{P1}) \quad \min_{a_{i,j}, \beta_{i,j}^r, P_{i,j}^r} \ T_i^{RRH}$$

subject to:

$$\text{C1:} \quad \sum_{i=1}^{\mathcal{N}} a_{i,j} = 1, \quad \forall j \in \mathcal{K},$$

$$\text{C2:} \quad \sum_{r=1}^{\mathcal{R}} a_{i,j} \beta_{i,j}^r \leq 1, \quad \forall i, j,$$

$$\text{C3:} \quad a_{i,j} \beta_{i,j}^r \gamma_{i,j}^r > \gamma^{th},$$

$$\text{C4: } a_{u,i}\beta^r_{u,i} + a_{v,i}\beta^r_{v,i} \leq 1, \quad \forall r \in \mathcal{R}, \ \forall (u,v) \in S_i,$$
$$\text{C5: } \sum_{j=1}^{\mathcal{K}} \sum_{r=1}^{\mathcal{R}} a_{i,j}\beta^r_{i,j} P^r_{i,j} \leq P_i^{max}, \quad \forall i \in \mathcal{N},$$
$$\text{C6: } \lambda_i^{RRH} \leq \mu_i^{RRH}, \quad \forall i \in \mathcal{N},$$
$$\text{C7: } a_{i,j}, \beta^r_{i,j} \in \{1,0\}, \quad \forall j \in \mathcal{K}, \ \forall r \in \mathcal{R},$$
$$\text{C8: } P^r_{i,j} \geq 0, \quad \forall r \in \mathcal{R}, \tag{18}$$

where C1 to C6 refer to the constraints (12) to (17), respectively. The constraint C7 represents that the decision variable for user association and RB allocation are the binary variables. Finally, C8 defines the non-negativity condition of the transmit power.

Corollary 1: The objective function in (18) and the constraints C6 and C7 turn the problem **P1** into a mixed integer non-linear program (MINLP) with the non-convex feasibility set. The optimization problem P1 is computationally intractable and is an NP-hard problem [22], [24].

C. Constraint Sets of Computing Resource Allocation

In order to ensure the minimum delay in baseband processing queue, assume that each RRH is connected to only one BBU server and each BBU server can utilize maximum number of U VMs. The BBU-RRH mapping constraints can be defined as follows:

- The constraint (19) ensures that each RRH is associated with only one VM in one BBU server, i.e.,
$$\sum_{m=1}^{M} b_{i,m} = 1, \quad \forall i \in \mathcal{N}. \tag{19}$$
- The constraint (20) ensures the maximum capacity limits of each BBU server as
$$\sum_{i=1}^{\mathcal{N}} b_{i,m} \leq U, \quad \forall m \in M. \tag{20}$$
- The constraint (21) maintains the queueing stability at each BBU, i.e., the arrival rate should not be greater than the service rate, which is
$$\lambda_m^{BBU} \leq \mu_m^{BBU}, \quad \forall m \in M. \tag{21}$$

Considering the aforementioned constraints, the computing resource allocation problem can be formulated as:

$$(\mathbf{P2}) \min_{b_{i,m}} T_m^{BBU}$$

subject to:

$$\text{C1: } \sum_{m=1}^{M} b_{i,m} = 1, \quad \forall i \in \mathcal{N},$$
$$\text{C2: } \sum_{i=1}^{\mathcal{N}} b_{i,m} \leq U, \quad \forall m \in M,$$
$$\text{C3: } \lambda_m^{BBU} \leq \mu_m^{BBU}, \quad \forall m \in M,$$
$$\text{C4: } b_{i,m} \in \{1,0\}, \quad \forall i \in \mathcal{N}, \ \forall m \in M. \tag{22}$$

where $b_{i,m}$ represents that the decision variable for BBU-RRH mapping is a binary variable.

Corollary 2: The objective function in (22) and the constraints C3 and C4 turn the problem **P2** into a mixed integer non-linear program (MINLP) with the non-convex feasibility set. The optimization problem **P2** is computationally intractable and is an NP-hard problem [22], [24].

IV. Relaxation to Fractional Resource Allocation

We relax the problem **P1** by replacing non-convex constraints with the convex constraints. First, we relax the constraint C7 by assuming the time sharing approach [29] of RB allocation, i.e., $0 \leq \beta^r_{i,j} \leq 1$. We introduce two new variables $\Gamma^r_{i,j} = a_{i,j} \times \beta^r_{i,j} \in (0,1]$ and $\mathcal{A}^r_{i,j} = \Gamma^r_{i,j} \times P^r_{i,j} \in (0,1]$. $\Gamma^r_{i,j}$ represents both user association and sharing factor of resource block. It denotes the portion of time the RB r is allocated to the user j and RRH i link. $\mathcal{A}^r_{i,j}$ denotes the actual transmit power of SUE j on RB r. Since the interference can be centrally coordinated among the RRHs through the centralized BBU pool, we relax the constraint C6 by assuming no interference, $\gamma^r_{i,j} = \frac{|h^r_{i,j}|P^r_{i,j}}{\eta_0} = \delta^r_{i,j}P^r_{i,j} = \frac{\delta^r_{i,j}\mathcal{A}^r_{i,j}}{\Gamma^r_{i,j}}$, where the service rate of each RRH becomes $\mu_i^{RRH} = \Delta B \sum_{j=1}^{\mathcal{K}} \sum_{r=1}^{\mathcal{R}} \Gamma^r_{i,j} \log_2(1 + \frac{\delta^r_{i,j}\mathcal{A}^r_{i,j}}{\Gamma^r_{i,j}})$. The primary formulation in **P1** can be expressed in an equivalent form by including new sets of variables $\Gamma^r_{i,j}$ and $\mathcal{A}^r_{i,j}$. The relaxed problem can be represented by:

$$(\mathbf{P3}) \max_{\Gamma^r_{i,j}, \mathcal{A}^r_{i,j}} \mu_i^{RRH} - \lambda_i^{RRH}$$

subject to:

$$\text{C1: } \sum_{i=1}^{\mathcal{N}} \frac{\Gamma^r_{i,j}}{\beta^r_{i,j}} = 1, \quad \forall j \in \mathcal{K},$$
$$\text{C2: } \sum_{r=1}^{\mathcal{R}} \Gamma^r_{i,j} \leq 1, \quad \forall i,j,$$
$$\text{C3: } -\mathcal{A}^r_{i,j}\delta^r_{i,j} + \gamma^{th} \leq 0,$$
$$\text{C4: } \Gamma^r_{u,i} + \Gamma^r_{v,i} \leq 1, \quad \forall r \in \mathcal{R}, \ \forall (u,v) \in S_i,$$
$$\text{C5: } \sum_{j=1}^{\mathcal{K}} \sum_{r=1}^{\mathcal{R}} \mathcal{A}^r_{i,j} \leq P_i^{max}, \quad \forall i \in \mathcal{N},$$
$$\text{C6: } \lambda_i^{RRH} \leq \mu_i^{RRH}, \quad \forall i \in \mathcal{N},$$
$$\text{C7: } \beta^r_{i,j} \in (0,1], \quad \forall j \in \mathcal{K}, \ \forall r \in \mathcal{R}. \tag{23}$$

As the number of resource blocks becomes relatively large, the duality gap of any optimization problem satisfying time sharing condition becomes negligible [30]. The solution of relaxed optimization problem **P3** is asymptotically optimal since it satisfies the time sharing condition [29].

Corollary 3: The relaxed optimization problem **P3** is convex; the objective function is concave and all the constraints are affine.

Since **P3** is a non-linear convex problem, the interior point methods can be used solve this problem [31]. To observe the nature of RB and power allocation, we formulate an equivalent problem **P3** as a base and use Karush-Kuhn-Tucker (KKT) optimality and define the following Lagrangian function:

$$
\begin{aligned}
&\mathbb{L}(\Gamma, \mathcal{A}, \sigma, \varsigma, \upsilon, \phi, \varphi, \psi) \\
&= \Delta B \sum_{j=1}^{\mathcal{K}} \sum_{r=1}^{\mathcal{R}} \Gamma_{i,j}^r \log_2 \left(1 + \frac{\delta_{i,j}^r \mathcal{A}_{i,j}^r}{\Gamma_{i,j}^r}\right) - \sum_{j=1}^{K} \lambda_j^{SUE} \\
&\quad + \sum_{j=1}^{\mathcal{K}} \sigma_j \left(1 - \sum_{i=1}^{\mathcal{N}} \frac{\Gamma_{i,j}^r}{\beta_{i,j}^r}\right) + \sum_{j=1}^{\mathcal{K}} \sum_{i=1}^{\mathcal{N}} \varsigma_{i,j} \left(1 - \sum_{r=1}^{\mathcal{R}} \Gamma_{i,j}^r\right) \\
&\quad + \sum_{r=1}^{\mathcal{R}} \upsilon_r (0 + \mathcal{A}_{i,j}^r \delta_{i,j}^r - \gamma^{th}) \\
&\quad + \sum_{i=1}^{\mathcal{N}} \sum_{r=1}^{\mathcal{R}} \phi_{i,r} (1 - \Gamma_{u,i}^r - \Gamma_{v,i}^r) \\
&\quad + \sum_{i=1}^{\mathcal{N}} \varphi_i \left(P_i^{max} - \sum_{j=1}^{\mathcal{K}} \sum_{r=1}^{\mathcal{R}} \mathcal{A}_{i,j}^r\right) \\
&\quad + \sum_{i=1}^{\mathcal{N}} \psi_i \left(\Delta B \sum_{j=1}^{\mathcal{K}} \sum_{r=1}^{\mathcal{R}} \Gamma_{i,j}^r \log_2 \left(1 + \frac{\delta_{i,j}^r \mathcal{A}_{i,j}^r}{\Gamma_{i,j}^r}\right)\right. \\
&\quad \left. - \sum_{j=1}^{K} \lambda_j^{SUE}\right), \qquad (24)
\end{aligned}
$$

where φ, and ψ are the vectors of Lagrange multipliers associated with power and queueing stability requirements for cellular and SUEs, respectively. Similarly, $\sigma, \varsigma, \upsilon, \phi$ are the Lagrange multipliers for the constraints C1-C4. Differentiating (24) with respect to $\mathcal{A}_{i,j}^r$, we obtain the following power allocation of SUE i over RB r as

$$P_{i,j}^r = \frac{\mathcal{A}_{i,j}^r}{\Gamma_{i,j}^r} = \left[\xi - \frac{1}{\delta_{i,j}^r}\right]^+, \qquad (25)$$

where $\xi = \frac{\Delta B(1+\psi_i)}{\ln(\varphi_i - \upsilon_r \delta_{i,j}^r)}$ and $[\varepsilon]^+ = \max(\varepsilon, 0)$, which is a multi-level water filling allocation [29].

Proof: See **Appendix A.** ■

Although we have obtained a closed-form solution for optimal power allocation using Lagrange multipliers, it is still difficult to solve for optimal radio resource allocation from (24) due to the mathematical intractability. In the next section, we present an auction based distributed solution that satisfies all the constraints of the original problems **P1** and **P2** under the assumption that the system is feasible given the network size, number of RBs and SINR threshold value.

V. Double-Sided Auction Based Distributed Resource Allocation (DS-ADRA)

The objective of our proposed solution is to optimize the mean response time in a C-RAN system in terms of solving communication and computing resource allocation along with user association, and BBU-RRH mapping in C-RANs. To solve the communication and computing resource optimization problem, in this section, we propose a joint resource allocation solution using the DS-ADRA method, where small cell base stations and users jointly participate using the concept of auction theory.

A. User Association and Communication Resource Allocation

In the auction based resource allocation procedure, we assume that small cell users (e.g., SUEs) and small cell base stations (e.g., SBS/RRH) are the agents. An auctioneer or cloud controller (CC) is a software defined module, which resides in the BBU pool for controlling resources in the C-RAN. It is assumed that all SUEs and RRHs within the C-RAN are always connected to the auctioneer using the control plane. The exchange of bidding information among the SUEs, RRHs and the BBU pool are done through the control plane. When the communication and computing resource allocations are done using the auction procedure, the SUEs setup the data plane to the selected RRHs and start data transmission. The exchange of bidding information and the detailed auction procedure are illustrated in Fig. 5 and given as follows:

Step 1: Whenever a user j receives the pilot signal from base stations, it generates a bid information and sends this information to base stations through the auctioneer. The bid information contains two types of information, i.e., F_j^1 and F_j^2. F_j^1 represents the data rate requirement based on which applications are running on the user side, i.e., $F_j^1 = \lambda_j^{SUE}$. The data rate requirement (in bps) serves as an arrival rate to the base stations. The F_j^2 contains information about the candidate base station list. A base station becomes a candidate for users, when the following condition is satisfied:

$$
\begin{aligned}
F_j^2 &= \{a_{i,j}\} = [\mathbf{a}_j] = \mathbf{a}_j, \quad \forall i \in \mathcal{N} \\
a_{i,j} &= 1, \text{ when } \left(\frac{\pi r_{ij}^2}{\pi R_i^2}\right) \leq 1, \qquad (26)
\end{aligned}
$$

where r_{ij} represents the distance between SUE j and RRH i and R_i denotes the radius of i^{th} RRH. F_j^2 represents the column vector, i.e., $\mathbf{a}_j = [a_{1,j}, a_{2,j}..., a_{\mathcal{N},j}]^T$ of the user association matrix $\mathbf{A}$ define as

$$\mathbf{A} = \begin{pmatrix} a_{1,1} & a_{1,2} & .. & .. & a_{1,\mathcal{K}} \\ a_{2,1} & a_{2,2} & .. & .. & a_{2,\mathcal{K}} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ a_{\mathcal{N},1} & a_{\mathcal{N},2} & .. & .. & a_{\mathcal{N},\mathcal{K}} \end{pmatrix} \qquad (27)$$

The auctioneer receives requests from all SUEs and generates two types of information for each RRH. The first information contains the initial association vector for i^{th} RRH, i.e.,

$$F_i^1 = \{F_j^1\} = \{a_{i,j}\} = [\mathbf{a}_i] = \mathbf{a}_i, \quad \forall j \in \mathcal{K}. \qquad (28)$$

F_i^1 represents the row vector, i.e., $\mathbf{a}_i = [a_{i,1}, a_{i,2}..., a_{i,\mathcal{K}}]$ of the user association matrix $\mathbf{A}$. The second information contains the mean data rate requirements of each RRH, i.e.,

$$F_i^2 = \lambda_i^{RRH}. \qquad (29)$$

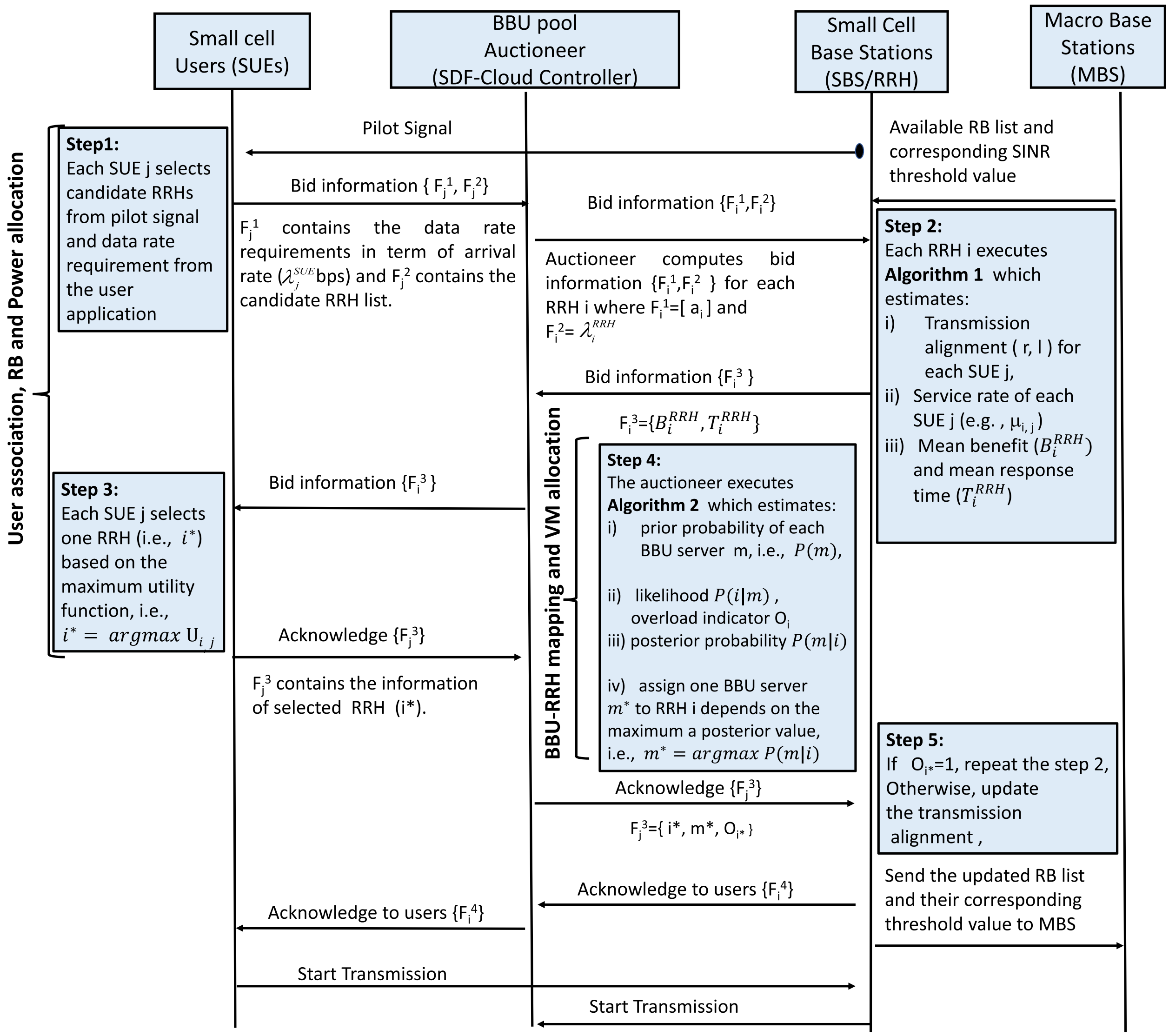

Fig. 5. Auction based distributed resource allocation method.

Step 2: The base station executes **Algorithm 1** to determine transmission alignment (r, l) (i.e., RB r and transmission power l) and the benefit for using (r, l). **Algorithm 1** satisfies all the constraints of problem **P1** to determine a stable allocation of transmission alignment for each user. The benefit of using (r, l) for SUE j associated with RRH i is defined as $\mathcal{B}_{i,j} = v_1 \mu_{ij}$, where v_1 is the bias factor for resource allocation in a small cell user. The benefit of RRH i can be defined as

$$\mathcal{B}_i^{RRH} = \sum_{j=1}^{\mathcal{K}} \mathcal{B}_{i,j} = v_1 \sum_{j=1}^{\mathcal{K}} \mu_{i,j} = v_1 \mu_i^{RRH}. \qquad (30)$$

If the base station finds a feasible assignment for users, it sends the bid information, i.e., $F_i^3 = \{\mathcal{B}_i^{RRH}, T_i^{RRH}\}$ to users which contains the expected service rate and mean response time of the base station.

Proposition 1: The transmission alignment (r, l) performed by **Algorithm 1** leads to a stable allocation.

Proof: Depending on the initial user association vector $\mathbf{a}_i$, the total power of RRH i is equally allocated among users at the initial stage of **Algorithm 1** to maintain the constraint **C5** in **P1**. An RB $r \in \mathcal{R}$ is selected for the user when it satisfies the RB association and SINR constraints (Line 9 and 11 in **Algorithm 1**). Let us assume that the transmission alignment (r, l) is allocated for user j by **Algorithm 1**. This allocation is stable since the same RB r cannot be selected by another user j'. Line 9 in **Algorithm 1** blocks the selection of r for user j'. Therefore, the transmission alignment (r, l) leads to a stable allocation. ■

Proposition 2: The communication resources allocation performed by **Algorithm 1** terminates after some finite number of steps.

Proof: Let the finite set $\{\beta_i\}$ denote all possible combinations of users and RBs matching for RRH i, where each element $\beta_{i,j}^r \in \{\beta_i\}$ denotes the RB r is allocated to the user j in RRH i. Since constraints **C2** and **C4** of **P1** are applied in **Algorithm 1**, no users select the same RB more than once. Therefore, the

Algorithm 1: Communication Resource Allocation for i^{th} RRH.

Input: Receives bid information F_i^1 and F_i^2, containing the information about the initial user association ($\mathbf{a}_i$), average arrival rate (λ_i^{RRH}), available RBs and corresponding threshold value (γ^{th})
Output: Returns the bid information F_i^3 which represents the total benefit ($\mathcal{B}_i^{RRH}$) and mean response time (T_i^{RRH}) for i^{th} RRH

I. Initialization: From initial user association matrix $\mathbf{A}$, the i^{th} RRH counts the total number of user requests and sets equal power level for each user $P_{i,j} = \frac{P_i^{max}}{\sum_{j=1}^{\mathcal{K}} a_{i,j}}$
$\mu_i^{RRH} \leftarrow \infty$
$\beta_{i,j}^r \leftarrow 0$
II. Iteration:
for $j \leftarrow 1$ ***to*** $\mathcal{K}$ **do**
  if $\mu_i^{RRH} > \lambda_i^{RRH}$ **then** // Check constraint C6 in equation (17)
    if $a_{i,j} == 1$ **then**
      for $r \leftarrow 1$ ***to*** $\mathcal{R}$ **do**
        if $\beta_{i,j}^r == 0$ **then** // Check constraint C2 and C4
          Estimate $\gamma_{i,j}^r$ using equation (6)
          if $\gamma_{i,j}^r >= \gamma^{th}$ **then** // Check constraint C3
            $\beta_{i,j}^r \leftarrow 1$
            $a_{i,j} \leftarrow 1$
            Estimate service rate of each user ($\mu_{i,j}$) and mean service rate of RRH (μ_i^{RRH}) using equations (7) and (8)
            Calculate response time of RRH (T_i^{RRH}) using equation (2)
            break;
      else
        $a_{i,j} \leftarrow 0$
        $\mu_{i,j} \leftarrow 0$
Estimate $\mathcal{B}_i^{RRH}$ and T_i^{RRH} using equations (30) and (2)
return $\mathcal{B}_i^{RRH}$ *and* T_i^{RRH}

finiteness of the set $\{\beta_i\}$ ensures the termination of **Algorithm 1** in finite number of steps. ■

Step 3: Each SUE calculates own utility function, i.e., $\mathcal{U}_{ij} = [\mathcal{B}_i^{RRH} - \lambda_j^{SUE}]^+ = [\mu_i^{RRH} - \lambda_j^{SUE}]^+$, where $[.]^+ = \max\{0; \}$. This means if $\lambda_j^{SUE} > \mu_i^{RRH}$, then the utility set is zero ($\mathcal{U}_{ij} = 0$). Each SUE can choose one RRH (i^*) based on the maximum utility function, i.e.,

$$i^* = \arg\max \mathcal{U}_{ij}, \quad \forall i \in \mathcal{N}. \tag{31}$$

The SUE j acknowledges the selected RRH (i^*) by sending acknowledgement message F_j^3.

Proposition 3: The equilibrium assignment holds for user j when $\mathcal{U}_{ij} \geq \max_{i \neq i', i \in \mathcal{N}} \{\mathcal{U}_{i'j}\}$ is satisfied for all RRHs.

Proof: See **Appendix B**.

B. Maximum A Posterior Probability (MAP) Based BBU-RRH Mapping and Computing Resource Allocation

Step 4: In the auction procedure, we assume that the auctioneer, i.e., SDF-cloud controller is always connected to the RRHs, which in turn collects and analyses all the bid information among the SUEs and RRHs. Based on the bid information $F_i^3 = \{\mathcal{B}_i^{RRH}, T_i^{RRH}\}$, and the acknowledgement message $F_j^3 = i^*$, the cloud controller executes **Algorithm 2** which determines the posterior probability based BBU-RRH association value, where each RRH can be associated with one BBU server and utilizes VMs for baseband processing depending on the expected service rate and BBU capacity information.

Algorithm 2: Computing Resource Allocation for i^{th} RRH.

Input: Receives the service rate (μ_i^{RRH}) and mean response time (T_i^{RRH}) from the bid information F_i^3.
Output: Returns BBU association (e.g., $[b_i] = b_{i,m}, \forall m \in M$) and overload indicator flag (O_i) for RRH i

I. Initialization: Initialize total number (M), maximum capacity (U) and mean service rate (μ_m^{RRH}) of each BBU
$b_{i,m} \leftarrow 0$
II. Iteration:
for $t \leftarrow 1$ ***to*** T **do**
  for $m \leftarrow 1$ ***to*** M **do** // i) Prior estimation
    if $t == 1$ **then**
      $\mathcal{C}_m(t) = U$
      $P(m) = 1/\mathcal{C}_m(t)$
    else
      $q_m(t) = \mathcal{C}_m(t-1) - \sum(b(:,m) == 1)$
      if $q_m(t) <= 0$ **then**
        $P(m) = \epsilon$
      else
        $P(m) = 1/q_m(t)$
    if $\mu_i^{RRH} \leq \mu_m^{BBU}$ **then** // ii) Likelihood estimation
      $L(i,m) = \frac{\mu_i^{RRH}}{\mu_m^{BBU}}$
      $P(i,m) = \frac{L(i,m)}{\sum_{\forall m} L(i,m)}$ using equation (33)
      $O_i = 0$
    else
      $L(i,m) = 0$
      $P(i,m) = 0$
      $O_i = 1$ // Set the overflow flag
  for $m \leftarrow 1$ ***to*** M **do** // iii) Posterior estimation
    $T(m) = T(m) + P(i,m) * P(m)$
    $Post(m,i) = \frac{P(i,m)P(m)}{T(m)}$ using equation (34)
  // iv) BBU-RRH mapping and VMs allocation
  $[V, M] = max(Post(:,i))$
  $m = index(M)$
  $feasibility = \mathcal{C}_m(t)$
  if $feasibility > 0$ **then**
    $b(i,m) = 1$
    $\mathcal{C}_m(t+1) = \mathcal{C}_m(t) - 1$
  else
    $\mathcal{C}_m(t+1) = \mathcal{C}_m(t)$
return $[b_i]$ *and* O_i

Assuming that the expected service rate μ_i^{RRH} of the i^{th} RRH is known based on the benefit information of bid F_i^3, the MAP based BBU-RRH mapping operates as follows:

- Feasibility and Prior Probability: The auctioneer determines which BBU server becomes feasible for RRH i. Using the BBU capacity, U, and BBU-RRH association information, the feasibility of each BBU server is determined at time t by:

$$q_m(t) = U - \sum_{i=1}^{\mathcal{N}} b_{i,m}.$$

The prior probability of each BBU server is estimated according to their feasibility information. The prior probability of m^{th} BBU can be estimated as

$$P(m) = \begin{cases} \frac{1}{q_m(t)}, & q_m(t) \neq 0 \\ \epsilon, & \text{otherwise.} \end{cases} \quad (32)$$

- Likelihood: The likelihood is estimated as per BBU server basis. For a given BBU m, the likelihood of RRH i^* can be estimated as

$$P(i^*|m) = \begin{cases} \frac{L(i^*|m)}{\sum_{\forall m} L(i^*|m)}, & \text{if } \mu_{i^*}^{RRH} \leq \mu_m^{BBU} \\ 0, & \mu_{i^*}^{RRH} > \mu_m^{BBU}, \\ & \text{sets } O_{i^*} = 1, \end{cases} \quad (33)$$

where $L(i^*|m)$ can be estimated as

$$L(i^*|m) = \begin{cases} \frac{\mu_{i^*}^{RRH}}{\mu_m^{BBU}}, & \text{if } \mu_{i^*}^{RRH} \leq \mu_m^{BBU} \\ 0, & \mu_{i^*}^{RRH} > \mu_m^{BBU}. \end{cases}$$

When the likelihood becomes zero ($P(i^*|m) = 0$), the auctioneer sets the overload indicator flag to one, i.e., $O_{i^*} = 1$, and adds this information to the acknowledgement message F_j^3. The overload indicator flag helps to determine which RRH is overloaded with user access requests.
- Posterior Probability: Posterior probability refers to the selection probability of BBU m given by RRH i^*. According to Bayes' rule, we formulate the posterior probability of $P(m|i^*)$ as follows:

$$P(m|i^*) = \frac{P(i^*|m)P(m)}{p(x)}, \quad (34)$$

where $p(x)$ is $p(x) = \sum_{m \in M} P(i^*|m)P(m)$.
- BBU Association and VM Allocation: The auctioneer selects BBU m^* for RRH i^* according to their maximum a posterior probability values; that is, $m^* = \arg\max P(m|i^*)$, and assigns one VM for the RRH i^* to process baseband operation. It updates the BBU-RRH association parameter $b_{i^*,m^*} = 1$ and the feasibility of BBU server in next time slot (e.g., $q_{m^*}(t+1) = q_{m^*}(t) - 1$.
- The auctioneer adds the m^* and O_{i^*} information to the acknowledgement message F_j^3 and sends the messages to the corresponding RRH.

Step 5: If the RRH finds that the overload indicator flag is set, it repeats the step 2, otherwise sends an acknowledgement message to the users. The RRH updates the transmission alignment and sends the allocated RB list and corresponding new SINR threshold value to the MBS.

VI. Simulation Results

In this section, the performance of the proposed DS-ADRA is investigated. In the simulation model, as shown in Fig. 6, we consider a 120 m×100 m area, where one macro base station is underlaid by 6 to 10 small cell base stations. The locations of RRHs, SUEs and MUEs are modeled using spatial Poisson point process (PPP) with predefined intensity values. The settings for the simulation parameters are shown in Table III. The simulations are averaged over 100 trials. The minimum data rate requirement is considered as the arrival rate of a user. According to the service rate of the entire C-RAN system, we define Jain's fairness index and the system efficiency, respectively, as

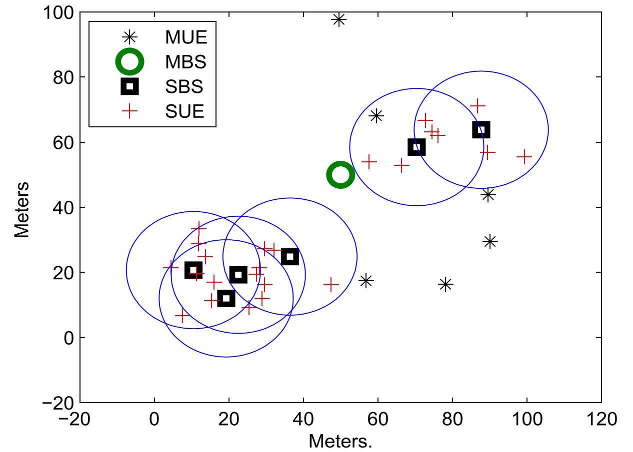

Fig. 6. Simulation environment.

TABLE III
Simulation Parameters

Parameters	Values
Total no. of small cells	$6 - 10$
Total no. SUEs	$10 - 100$
Total no. of RB	50
RB bandwidth	180 kHz
System bandwidth	10 MHz
Radius of small cell	10 m
Minimum data rate requirements	50-140 kbps
Number of MUEs	$10 - 20$
Transmission power of RRH	30 dBm
Path-loss exponent	4
Noise power spectrum density	-144 dBm/Hz

$$J = \frac{\left(\sum_{i=1}^{\mathcal{N}} \mu_i^{RRH}\right)^2}{\mathcal{N} \sum_{i=1}^{\mathcal{N}} (\mu_i^{RRH})^2},$$

and

$$E = \sum_{i=1}^{\mathcal{N}} \mu_i^{RRH}.$$

The performance of our proposed method is evaluated in terms of mean response time, system efficiency, sum data rate and Jain's fairness index for the entire C-RAN system. We also compare our proposed method with the centralized first-come-first-service (FCFS) [32] and the distributed SINR auction based RB allocation [12] methods. The centralized FCFS is the conventional method where each user selects the nearest base station depending on the relative signal strength. The base

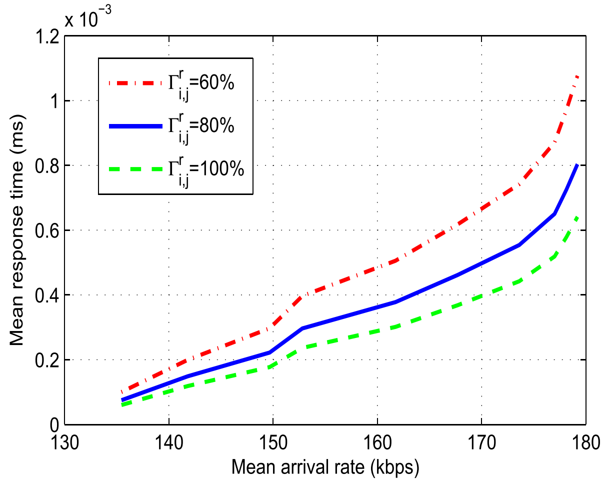

Fig. 7. Mean response time performance of DS-ADRA method with three different percentages of bandwidth utilization.

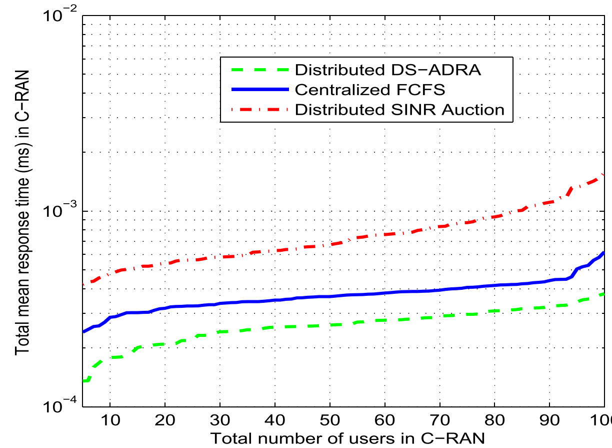

Fig. 8. Mean response time performance among DS-ADRA, centralized-FCFS and SINR auction with different number of users when $\mathcal{N} = 6$, $\mathcal{R} = 100$ and $\gamma^{th} = 10$ dB.

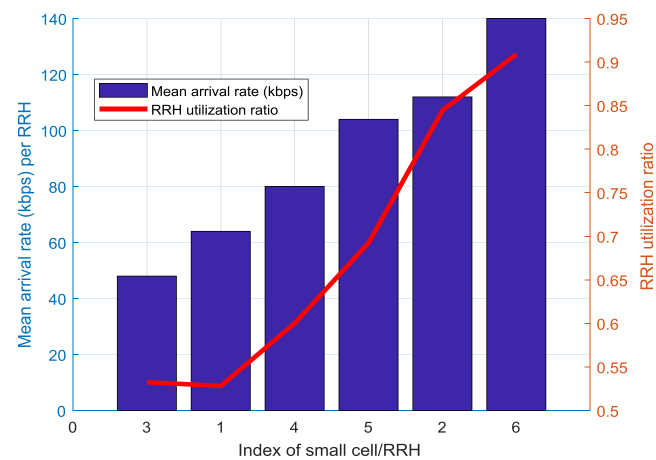

Fig. 9. RRH utilization ratio.

station allocates RBs to the users based on the SINR threshold value and first-come-first-service basis. On the other hand, the working procedure of SINR auction method is as follows:

- Step 1: The users work as bidders and all the base stations work as an auctioneer. At first, for all unallocated RBs, each user proposes its bid $SINR^{SUE}_{RB_1} \geq SINR^{SUE}_{RB_2}$ where $RB_1 \neq RB_2$.
- Step 2: The base station assigns RBs to the users according to these bids.
- Step 3: Each user cancels their bid to the allocated RBs, and repeats steps 1 and 2 until all RBs are allocated.

However, we modified the Steps 1 and 3 to make it compatible for comparison to our method, as follows:

- Step 1: For all unallocated RBs, each user proposes its bid $SINR^{SUE}_{RB_1} \geq SINR^{SUE}_{RB_2}$ where $SINR^{SUE}_{RB_1} \geq \gamma^{th}$, $SINR^{SUE}_{RB_2} \geq \gamma^{th}$ and $RB_1 \neq RB_2$.
- Step 3: Each user cancels their bid to the allocated RBs, and repeats steps 1 and 2 until the user data rate requirement is satisfied.

We investigate the mean response time performance of DS-ADRA method with respect to mean arrival rate and different percentages of bandwidth utilization as shown in Fig. 7. In the two-tier C-RAN system, we consider that SUE utilizes the RBs of MUE in an underlaid approach under the constraints C2, C3 and C4 of problem **P1**. In the DS-ADRA method, **Algorithm 1** satisfies all these constraints and determines transmission alignment in terms of RB and power for SUEs. Here, the bandwidth utilization is referred to as frequency reuse ratio of the C-RAN system. The system response time becomes the lowest when the bandwidth utilization is 100 percent compared to 60 and 80 percent utilization as shown in Fig. 7. It can also be observed that the mean response time of the C-RAN system increases with the mean arrival rate.

Fig. 8 shows the mean response time performance comparison of the DS-ADRA, centralized FCFS, and SINR auction methods with respect to various number of SUEs in the C-RAN. It is shown that the DS-ADRA method outperforms the other methods. This due to the fact that in step 2 of **Algorithm 1**, DS-ADRA method estimates the transmission alignment, service rate, mean benefit and mean response time for SUEs. Depending on these information, in step 3 of DS-ADRA method, each SUE selects the best RRH which gives the maximum benefit in terms of service rate and response time for data transmission. On the other hand, in the centralized FCFS method, SUEs select one of the closest proximity RRHs and the selected RRH assigns RBs to the SUEs based on the FCFS policy and the SINR threshold. Also, the mean response time performance of the distributed SINR auction method is worse than the others due to the conflict choice of RBs. In this method, each user chooses RBs regardless of other users' choice. The same RBs are selected by many users, but in the end, one user becomes the winner. Moreover, in the RB selection, the users only check the SINR constraint.

Fig. 9 shows the RRH utilization ratios and mean arrival rates in each RRH. It is evident that RRH utilization depends on the incoming requests. The simulation results in Fig. 9 justify that RRH utilization increases with mean arrival rate. The RRH index with 6 has the highest utilization since the highest arrival rate

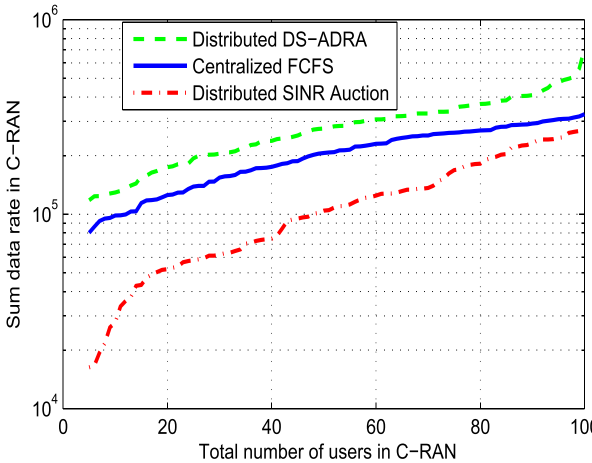

Fig. 10. C-RAN system efficiency with different number of users when $\mathcal{N} = 6$, $\mathcal{R} = 100$, and $\gamma^{th} = 10$ dB.

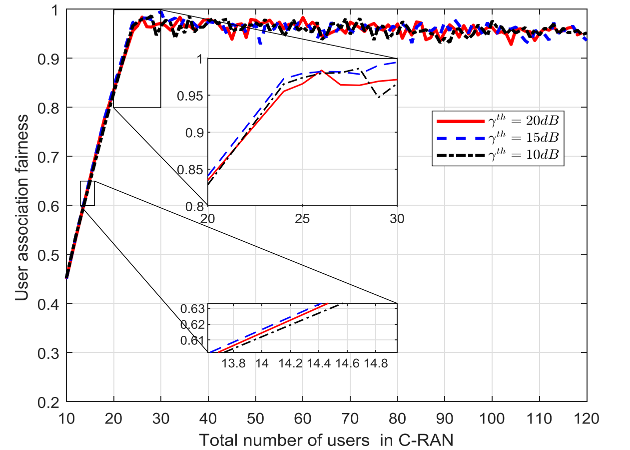

Fig. 12. Convergence of stable allocation of Algorithm 1 shown with UA fairness considering different SINR threshold values when $\mathcal{N} = 6$, $\mathcal{R} = 100$, and $\mathcal{K} = 100$.

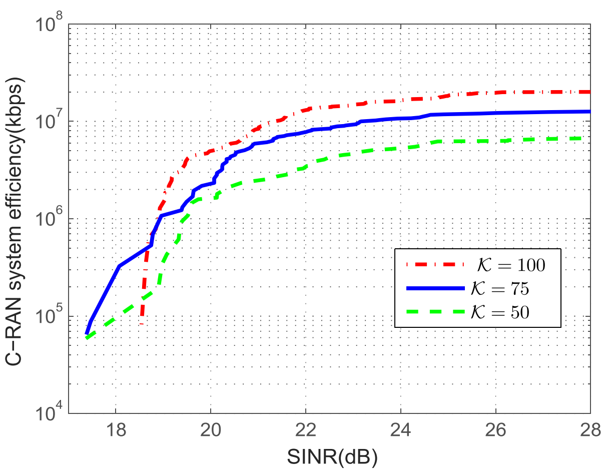

Fig. 11. C-RAN system efficiency of DS-ADRA with respect to achievable SINR with $\Gamma_{ij}^{r} = 100\%$ of bandwidth utilization when $\mathcal{N} = 6$, $\mathcal{R} = 100$ and $\gamma^{th} = 10$ dB.

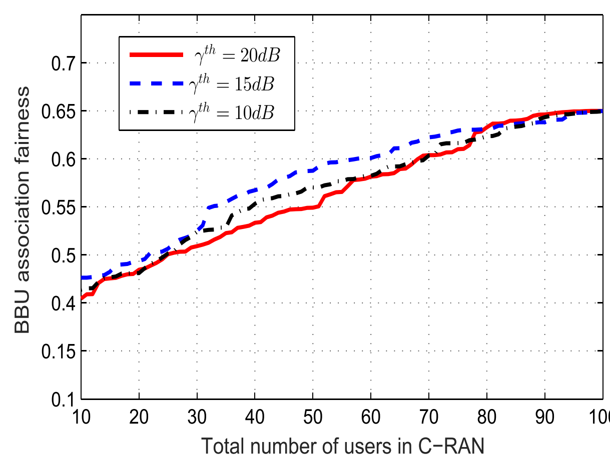

Fig. 13. Convergence of VM allocation of Algorithm 2 considering different SINR threshold values when $\mathcal{N} = 6$, $\mathcal{R} = 100$, $\mathcal{K} = 100$, $M = 4$, and $U = 3$.

140 kbps occurs at this base station compared to the other base stations.

Next, we investigate the C-RAN system efficiency performance of DS-ADRA, centralized FCFS, and SINR auction methods with respect to different number of users as shown in Fig. 10. The RRHs in C-RAN utilize 100 percent bandwidth. The system efficiency of all three methods increases with increasing number of users. Among them, the DS-ADRA performs the best due to the distributed nature of RB allocation (i.e., **Algorithm 1**) and RRH selection (i.e., Step 3 in DS-ADRA). In the DS-ADRA method, users are associated with RRHs based on the maximum utility, however, the centralized method utilizes relative signal strength and closer proximity RRHs and FCFS policy for users which limits the system efficiency of the C-RAN. Moreover, Fig. 11 shows the C-RAN system efficiency of DS-ADRA with respect to achievable SINR and different numbers of SUEs. In this scenario, equal SINR threshold level is considered as in **Algorithm 1,** that is 10 dB. The RRHs in C-RAN are allowed to utilize 100 percent bandwidth. It is observed from the figure that the system efficiency increases with the achievable SINR and number of SUEs. This is justifiable since the interference threshold levels that SUEs can tolerate decrease as sum rate increases. After we reach a certain SINR, that is 25dB, the system efficiency does not change significantly because of the limited number of RBs and SINR threshold value. Therefore, the curves stabilize depending on the total number of RBs.

The convergence behaviors of **Algorithm 1** and **Algorithm 2** in DS-ADRA method are shown with the fairness index in Fig. 12 and Fig. 13, respectively. According to the perspective of Jain's index, a larger J represents a fair allocation [33]. Fig. 12 shows that **Algorithm 1** converges and shows fair allocation despite different threshold values. Similarly, Fig. 13 shows that **Algorithm 2** finds a fair allocation of VMs for small cells within a finite number of steps regardless of different SINR threshold values.

VII. Conclusion

In this paper, we proposed an auction based distributed communication and computing resource allocation method for two-tier OFDM based delay aware C-RAN systems. The proposed DS-ADRA method satisfies the user association, BBU-RRH mapping, resource allocation and maximum power constraints as well as the queuing stability constraint. In addition, the DS-ADRA method associates one user with one RRH and assigns RRH to BBU pool based on the co-operative decision among users and RRH with the help of SDF C-RAN controller. In terms of mean response time and system efficiency, the proposed DS-ADRA method outperforms the centralized FCFS and SINR auction methods, due to the distributed nature of communication resource allocation (i.e., **Algorithm 1**), maximum utility based RRH selection, and posterior probability based computing resource allocation (i.e., **Algorithm 2**) being jointly executed in the DS-ADRA method. Furthermore, the proposed **Algorithm 1** and **Algorithm 2** ensure to converge to a stable allocation despite different arrival rates of users and SINR values of the C-RAN systems. The results show that the performance of the proposed DS-ADRA method becomes the best when the system supports 100 percent bandwidth utilization.

Appendix

A. The dual problem of (24) is:

$$\begin{aligned}
&\mathbb{D}(\sigma,\varsigma,\upsilon,\phi,\varphi,\psi)\\
&=\max_{\Gamma,\mathcal{A}} \Delta B\sum_{j=1}^{\mathcal{K}}\sum_{r=1}^{\mathcal{R}}\Gamma_{i,j}^{r}\left(1+\sum_{i=1}^{\mathcal{N}}\psi_i\right)\log_2\left(1+\frac{\delta_{i,j}^{r}\mathcal{A}_{i,j}^{r}}{\Gamma_{i,j}^{r}}\right)\\
&-\sum_{i=1}^{\mathcal{N}}\varphi_i\sum_{j=1}^{\mathcal{K}}\sum_{r=1}^{\mathcal{R}}\mathcal{A}_{i,j}^{r}-\left(1+\sum_{i=1}^{\mathcal{N}}\psi_i\right)\sum_{j=1}^{\mathcal{K}}\lambda_j^{SUE}\\
&-\sum_{j=1}^{\mathcal{K}}\sigma_j\sum_{i=1}^{\mathcal{N}}\frac{\Gamma_{i,j}^{r}}{\beta_{i,j}^{r}}-\sum_{j=1}^{\mathcal{K}}\sum_{i=1}^{\mathcal{N}}\varsigma_{i,j}\sum_{r=1}^{\mathcal{R}}\Gamma_{i,j}^{r}+\sum_{r=1}^{\mathcal{R}}\upsilon_r\mathcal{A}_{i,j}^{r}\delta_{i,j}^{r}\\
&-\sum_{i=1}^{\mathcal{N}}\sum_{r=1}^{\mathcal{R}}\phi_{i,r}(\Gamma_{u,i}^{r}+\Gamma_{v,i}^{r})+\sum_{i=1}^{\mathcal{N}}\varphi_iP_i^{max}+\sum_{j=1}^{\mathcal{K}}\sigma_j\\
&+\sum_{j=1}^{\mathcal{K}}\sum_{i=1}^{\mathcal{N}}\varsigma_{i,j}-\sum_{r=1}^{\mathcal{R}}\upsilon_r\gamma^{th}+\sum_{i=1}^{\mathcal{N}}\sum_{r=1}^{\mathcal{R}}\phi_{i,r} \qquad (35)
\end{aligned}$$

Considering only the power allocation (e.g., $\mathcal{A}_{i,j}^{r}$) part from (35):

$$\begin{aligned}
Ł(\mathcal{A}_{i,j}^{r}) &= \Delta B\sum_{j=1}^{\mathcal{K}}\sum_{r=1}^{\mathcal{R}}\Gamma_{i,j}^{r}\left(1+\sum_{i=1}^{\mathcal{N}}\psi_i\right)\\
&\times\log_2\left(1+\frac{\delta_{i,j}^{r}\mathcal{A}_{i,j}^{r}}{\Gamma_{i,j}^{r}}\right)\\
&-\sum_{i=1}^{\mathcal{N}}\varphi_i\sum_{j=1}^{\mathcal{K}}\sum_{r=1}^{\mathcal{R}}\mathcal{A}_{i,j}^{r}+\sum_{r=1}^{\mathcal{R}}\upsilon_r\mathcal{A}_{i,j}^{r}\delta_{i,j}^{r}
\end{aligned}$$

Maximizing **P3** for any given $\Gamma_{i,j}^{r}$ is equivalent to differentiating $Ł(\mathcal{A}_{i,j}^{r})$ with respect to $\mathcal{A}_{i,j}^{r}$ and setting the result to zero. That is

$$\begin{aligned}
&\frac{\partial Ł}{\partial\mathcal{A}_{i,j}^{r}}=0\\
&\frac{\Delta B\Gamma_{i,j}^{r}(1+\psi_i)}{\ln\left(1+\frac{\delta_{i,j}^{r}\mathcal{A}_{i,j}^{r}}{\Gamma_{i,j}^{r}}\right)}\frac{\delta_{i,j}^{r}}{\Gamma_{i,j}^{r}}-\varphi_i+\upsilon_r\delta_{i,j}^{r}=0\\
&P_{i,j}^{r^*}=\frac{\mathcal{A}_{i,j}^{r}}{\Gamma_{i,j}^{r}}=\left[\frac{\Delta B(1+\psi_i)}{ln(\varphi_i-\upsilon_r\delta_{i,j}^{r})}-\frac{1}{\delta_{i,j}^{r}}\right]^{+}.
\end{aligned}$$

B. *Proof of Proposition 3*

It can be proven that $\mathcal{U}_{ij}\geq\max_{i\neq i',i\in\mathcal{N}}\{\mathcal{U}_{i'j}\}$ satisfies if and only if the conditions

$$\mathcal{U}_{ij}=C_i, \qquad (36)$$

and

$$\mathcal{U}_{ij}\geq\max_{i\neq i',i\in\mathcal{N}}\{\mathcal{U}_{i'j}\} \qquad (37)$$

are satisfied for all i given that $i=\{F_j^1\in\{a_{i,j}\}\}$ and $\{a_{i,j}\}\neq 0$. If (36) is not satisfied, or equivalently, if there exists $i'\in F_j^1$ such that $\mathcal{U}_{i'j}\geq\mathcal{U}_{ij}$, that is $[\mathcal{B}_{i'}^{RRH}-\lambda_{i'j}]^{+}\geq[\mathcal{B}_{i}^{RRH}-\lambda_{ij}]^{+}$, where data rate requirement of user j is same for both RRHs, i.e., $\lambda_{i'j}=\lambda_{ij}=\lambda_j^{SUE}$, then user j selects i' in Step 3 in DS-ADRA procedure based on the maximum utility.

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