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Energy-efficient resource allocation and RRH association in multitier 5G H-CRANs

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Abstract

The rapid growth of connected devices and multimedia applications intensify the needs of high data rate and energy-efficient networks. Multitier heterogeneous cloud radio access networks have been presented as a capable candidate for fifth-generation networks for much higher data rate and energy efficiency (EE) than fourth generation. Therefore, in this paper, we consider the EE maximization in the uplink of a single-carrier frequency division multiple access–based multitier heterogeneous cloud radio access network. We formulate a joint subchannel assignment, power allocation, and remote radio head association problem for EE maximization. Single-carrier frequency division multiple access introduces subchannel exclusivity and subchannel adjacency constraints. These constraints, respectively, ensure the allocation of a subchannel to a single user at a time and the allocation of multiple subchannels to a user only if they are adjacent. In addition, we put constraints on each user's minimum data rate and maximum transmit power. Due to the simultaneous consideration of these four constraints, the solution of the formulated problem becomes harder. Therefore, a three-step algorithm is developed, which solves this problem in an iterative manner. Simulation results verify that our proposed algorithm significantly improve the EE of the network.

1 | INTRODUCTION

Because of the speedy rise in the number of connected devices and multimedia applications, the mobile data traffic is exponentially increasing.[1] The statistical analysis and forecasts from International Telecommunication Union[2] reveals that the expected mobile and wireless data traffic will increase up to 1000 times by year 2025 with a further increase of 10 to 100 times from year 2020 to 2030. To handle this speedy increase in mobile and wireless data traffic, the existing fourth-generation cellular systems need to be evolved.[3] With the progress toward fifth generation, the existing cellular systems have transformed into multitier networks that contain a traditional macrocell network with different low-power small cells networks.[4] The dense deployment of small cells, which include picocelles and femtocells, in macrocell networks is one of the effective method to handle the speedy increase in mobile data traffic and high date rate demands.[5]

The main features of picocells include moderate transmit power, smaller coverage range, and the use of licensed spectrum,[5] while femtocells have very shorter range of communication with much lesser transmit power. In addition, femtocells are capable of delivering better quality of service (QoS) and higher throughput. However, the dense deployment of small cells makes the energy consumption and network operational as well as computational burden extremely high.[6] Resource allocation also becomes the key issue in such kind of multitier networks. To meet these challenges about

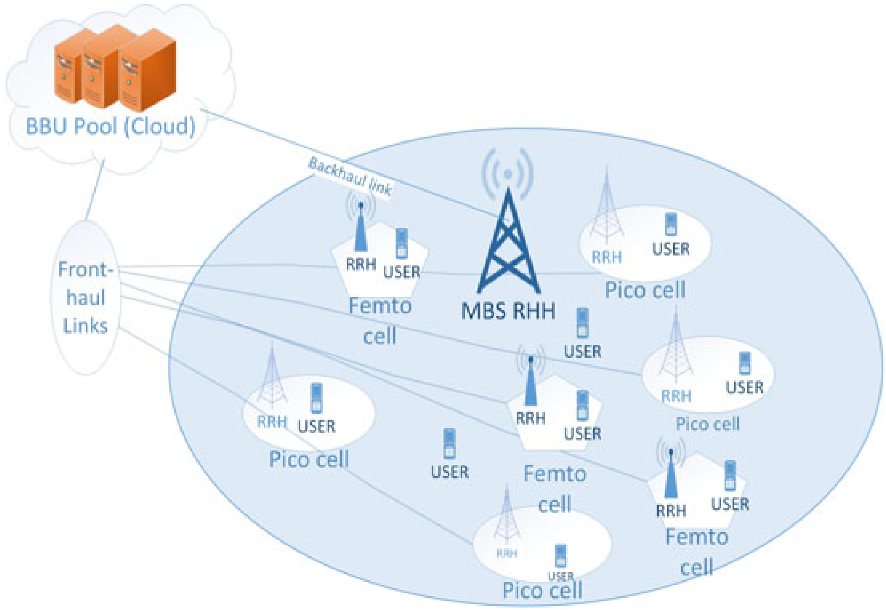

FIGURE 1 Illustration of a three-tier heterogeneous cloud radio access network. BBU, base band unit; MBS, macro base station; RRH, remote radio head

multitier networks, a new network model, known as heterogeneous cloud radio access networks (H-CRANs), has been presented.[7] An H-CRAN is shown in Figure 1, which contains a centralized base band unit (BBU) pool and a set of remote radio heads (RRHs), which are interconnected through the fronthaul links. The duties of RRHs include radio frequency transmitting and reception, while BBUs performs baseband signal processing and upper-layer functionalities.[8,9]

In the Third-Generation Partnership Project Long-Term Evolution-advanced, single-carrier frequency division multiple access (SC-FDMA) and orthogonal frequency division multiple access (OFDMA) have been considered as multiple access techniques for uplink (UL) and downlink (DL), respectively.[10] The reason behind considering SC-FDMA for UL communication is its lower peak-to-average power ratio than OFDMA. There are two ways to implement SC-FDMA, ie, distributed SC-FDMA and constrained SC-FDMA. In the former one, the subchannels of a user are spread over the complete signal band, while in the later one, users transmit their data symbols on an adjacent subchannel set. Furthermore, there are two constraints associated with constrained SC-FDMA, namely, subchannels exclusivity and subchannels adjacency. These constraints, respectively, ensure the allocation of a subchannel to one user at a time and the allocation of multiple subchannels to a user only if they are adjacent.[11] Tombaz et al[12] and Wong and Evans[13] verified that constrained SC-FDMA is better than distributed SC-FDMA in terms of throughput. Therefore, constrained SC-FDMA has been considered in this paper.

1.1 | Related work

Other works[14-17] considered transmit power minimization as the EE metric in OFDMA-based HetNets. In the work of Fei et al,[14] a multiobjective optimization theory-based power allocation (PA) problem is formulated for OFDMA-based networks for the objectives of both EE and interference mitigation. To maximize the EE of the network with multiple users, the joint resource block assignment, relay selection, and PA were studied in the work of Song et al,[15] while in the work of Sun et al,[16] the active subchannels and bits assigned to each resource block were optimized. Wang et al[17] presented an optimal PA scheme for EE maximization in cognitive radio network with limitations on interference level and total transmit power.

Previous works on energy-efficient resource allocation (RA) in SC-FDMA based HetNets[18-28] investigated different aspects of RA, eg, some of the works studied only PA,[18-24] which take transmit power minimization as EE or only subchannel assignment (SA),[25-27] which take bits/joule as EE. Dechene and Shami[18] studied the RA with synchronous hybrid automatic repeat request constraints, which focuses on improving the user's EE provided that the users avoid automatic repeat request blocking. In the work of Ruder et al,[19] for the objective of transmit power minimization, a joint RA and user pairing have been considered. Kalil et al[20] proposed power efficient scheduler that results in sum transmit power minimization of UL Long-Term Evolution system subject to guaranteeing the QoS constraints of the users while in the works of Ahmad et al,[21,22] the RA problem was formulated for the user's aggregate transmit power minimization provided that the users data rate requirements are satisfied. Ahmad et al[23] studied optimal PA in SC-FDMA–based HetNets for sum rate maximizing subject to the maximum allowed transmit powers. In the work of Ahmad,[24] PA problem was considered in the same network and objective as in the work of Ahmad et al[23] with arbitrarily distributed finite power inputs where the solution is achieved by utilizing the link between mutual information and minimum mean-square error. Tsiropoulou et al[25] developed a game-theoretic technique for SA, while in the works of Aijaz et al[26] and Triantafyllopoulou et al,[27] the authors presented invasive weeds optimization–based SA technique with statistical QoS restriction. Joint SA and PA was studied in the work of Zheng et al[28] for EE maximization. The authors developed a suboptimal SA and an optimal PA algorithms for UL SC-FDMA. The suboptimal SA with optimal PA performed better than the optimal PA with round-robin SA.

Due to the computational efficiency of cloud radio access networks (C-RANs), the authors targeted joint RAs in other works[29-35] for OFDMA-based C-RANs. In the work of Shi et al,[29] the authors jointly considered transmit power minimization and RRH association using beamforming provided that the users data rate requirement is guaranteed. Huang et al[30] and Yoon and Cho[31] also targeted EE maximization and proposed PA techniques for H-CRANs. A similar problem like in the work of Shi et al[29] has been investigated by Luo et al,[32] which jointly considered beamforming and RRH selection for both the DL and UL. Subchannel assignment was further studied in the work of Shi et al[29] for EE maximization of the C-RANs by jointly optimizing PA with beamforming. In the work of Tang et al,[33] RA, RRH activation, and beamforming are jointly optimized for transmit power minimization in C-RANs. The RRH association was further investigated in the work of Tran et al[34] for enhancing EE of C-RANs, while in the work of Peng et al,[35] the authors studied joint SA and PA technique in H-CRAN for the same objective as in the work of Tran et al.[34] In the work of Tran et al,[36] the authors have presented a nonorthogonal multiple-access technique for H-CRAN taking into consideration the power consumption of different RRHs types, backhauling power consumption, and practical channel modeling. The objectives of this work are network sum rate and spectrum efficiency improvement. Wang et al[37] presented an energy-efficient RA technique for H-CRAN. They have formulated a joint RA problem and split it into subproblems, namely, network-wide beamforming vectors optimization problem and BBU arrangement problem. The former is solved by weighted minimum mean-square error method, while the latter is reformulated as a bin packing problem aiming at decreasing the BBUs count to save extra energy. A slotted DL H-CRAN was considered in the work of Li et al[38] and RA and congestion control are jointly studied to explore the EE-guaranteed tradeoff between delay performance and throughput utility. The considered problem is expressed as a stochastic optimization, which enhances the average throughput utility and sustains the network stability, while a joint admission control, PA, and user association problem was formulated in the work of Ali et al[39] for sum rate maximization of H-CRAN. The formulated problem is mixed-integer nonlinear programming (MINLP) problem, which is generally NP-hard. Therefore, a linear programming-based outer approximation algorithm is presented that solved the formulated NP-hard problem. In our previous work,[40] we have considered sum rate maximization problem in multitier C-RAN and formulated a joint SA, PA, and RRH association (SAPARA) problem for network sum rate maximization.

1.2 | Contribution

The energy-efficient RA problems have been well studied for various systems, eg, other works[14-17] have considered energy-efficient RA in OFDMA-based HetNets, while previous works[18-28] were based on SC-FDMA-based HetNets. Furthermore, other works[29-39] have considered the energy-efficient RA problems in OFDMA-based C-RAN, except the work of Tran et al,[36] which is based on nonorthogonal multiple-access–based H-CRAN, while the work of Ali et al[40] considered network sum rate maximization in multitier C-RAN. Table 1 contains the summary of these works. There is no work in the literature considering EE in SC-FDMA-based multitier H-CRAN. Therefore, in this paper, we aim at the EE maximization in the UL of a multitier SC-FDMA-based H-CRAN. We consider bits/joule as the EE metric and formulate a joint SAPARA problem, which is MINLP problem. Due to the subchannels exclusivity, subchannels adjacency, minimum achieved data rate, and maximum power budget constraints, the solution of joint optimization problem becomes harder. Therefore, a three-step iterative algorithm is presented to solve this MINLP problem where SA and PA are carried in the first and second steps, respectively, while RRH association is carried out in the third step.

The reminder of this paper is organized as follows. System model of the multitier H-CRAN and problem formulation are presented in Section 2. Section 3 contains the presented three-step RA algorithm, while in Section 4, the simulations are discussed. Section 5 contains conclusion of this paper.

TABLE 1 Comparison among the related works for the same objective of energy efficiency maximization

Ref. No.	System	UL/DL	Multiple-Access Scheme	Resources Management
Fei et al[14] and Wang et al[17]	HetNets	UL	OFDMA	power allocation
Song et al[15]	HetNets	UL	OFDMA	Resource block assignment, relay selection, and power allocation
Sun et al[16]	HetNets	UL and DL	OFDMA	SA and bits assignment
Kalil and Shami[20]	HetNets	UL	SC-FDMA	power control
Other works[25-27]	HetNets	UL	SC-FDMA	SA
Shi et al[29] and Luo et al[32]	C-RANs	UL and DL	OFDMA	beamforming, RRH selection, and network transmit-power minimization
Wang et al[30] and Yoon and Cho[31]	C-RANs	DL	OFDMA	PA
Shi et al[29]	C-RANs	DL	OFDMA	PA with beamforming
Tang et al[33]	C-RANs	UL and DL	OFDMA	PA, RRH activation, and beamforming
Tran et al[34]	C-RANs	UL	OFDMA	RRH association
Peng et al[35]	Heterogeneous C-RANs	DL	OFDMA	SA and PA
Tran et al[36]	Heterogeneous C-RANs	DL	NOMA	PA
Wang et al[37]	Heterogeneous C-RANs	DL	OFDMA	Joint RRH antenna resource and the BBU scheduling.
Li et al[38]	Heterogeneous C-RANs	DL	OFDMA	Joint congestion control and resource optimization
Ali et al[39]	Heterogeneous C-RANs	UL and DL	OFDMA	Joint user association, admission control, and PA for throughput maximization
Our Paper	Heterogeneous C-RANs	UL	SC-FDMA	RRH association, SA, and PA

Abbreviations: BBU, base band unit; C-RAN, cloud radio access network; DL, downlink; OFDMA, orthogonal frequency division multiple access; PA, power allocation; RRH, remote radio head; SA, subchannel assignment; UL, uplink.

2 | SYSTEM MODEL AND PROBLEM FORMULATION

We consider the UL of multitier fifth-generation H-CRAN based on SC-FDMA, which comprises of M total RRHs, ie, femtocell RRHs, picocell RRHs, and macrocell RRH, which share the same spectrum resources, as shown in Figure 1. The transmit power of picocell RHHs is lower than the macrocell RRH, while the femtocell RHHs transmit very small power as compared with the macrocell RRH and picocell RRHs. Moreover, there are K total users, which are deployed randomly and B is the total bandwidth, which is divided in to N subchannels, each having equal bandwidth W. These N subchannels are orthogonally reused by the associated users of each RRH. However, all the subchannels are simultaneously reused at each RRH. Furthermore, it is assumed that a user can only be connected to one RRH and a user may be assigned with one or multiple subchannels as long as the combined transmit powers of a user on all its allocated sub channels does not surpass the maximum transmit power $p_k^{\max}$. The subchannel exclusivity and adjacency constraints are fulfilled. It is supposed that the complete channel information is available to each user.

Let $p_{k,n}$ be the kth user transmit power on nth subchannel, $|h_{k,n}^m|^2$ be the channel gain of kth user to RRH m on nth subchannel, $I_{k,n}^m$ be the interference from user k to RRH m on nth subchannel, and σ^2 be the noise. Then, signal-to-interference-plus-noise ratio of kth user to RRH m on subchannel n is modeled as follows:

$$\gamma_{k,n}^m = \frac{p_{k,n}\left|h_{k,n}^m\right|^2}{\sigma^2 + I_{k,n}^m}, \tag{1}$$

where

$$I_{k,n}^m = \sum_{l \neq k} p_{l,n}\left|h_{l,n}^m\right|^2, \tag{2}$$

while the total signal-to-interference-plus-noise ratio of user k on all its subchannels assigned by the RRH m is modeled as follows[26]:

$$\Gamma_k = \frac{1}{\left|N_k^m\right|} \sum_{n \epsilon N_k} \left(\gamma_{k,n}^m\right). \tag{3}$$

The user k attainable data rate can be represented as follows:

$$R_k^m = W\left|N_k^m\right| \log_2\left(1+\Gamma_k\right), \tag{4}$$

where N_k^m is the allocated subchannels set to the kth user connected to RRH m. The EE is described as the amount of bits transmitted per unit consumption of energy at the source end, which is given as follows:

$$\eta_k^m = \frac{R_k^m}{P_T^k}, \tag{5}$$

where P_T^k is the total energy consumption of user k connected to RRH m, which consists of two parts, the combined transmit powers on all its subchannels $\sum_{n\epsilon N_k^m} p_{k,n}$ and the circuit energy consumptions of user k connected to RRH m, $p_{ckt,k}^m$, that is experienced by signal processing and various circuit blocks at the transmitter.[41,42] $p_{ckt,k}^m$ further comprises of two parts, static and dynamic parts, which can be expressed as follows:

$$p_{ckt,k}^m = p_k^s + \varepsilon R_k^m, \tag{6}$$

where p_k^s represents the static part and εR_k^m represents dynamic power of user k, which is demonstrated as a linear function of attained data rate of the user. ε denotes the consumption of dynamic power per unit data rate. The EE of kth user connected to RRH m can be modeled as follows:

$$\eta_k^m = \frac{R_k^m}{\xi \sum_{n\epsilon N_k^m} p_{k,n} + p_k^s + \varepsilon R_k^m}, \tag{7}$$

where ξ represents the reciprocal of the power amplifier's drain efficiency.[41]

Furthermore, the RRH association matrix is expressed as $\alpha_{k,m}$ where

$$\alpha_{k,m} = \begin{cases} 1, & \text{if a user is connected to RRH } m \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

and the optimization problem is formulated as follows:

$$\max \quad \sum_{m=1}^{M} \sum_{k=1}^{K} \alpha_{k,m} \eta_k^m \tag{9}$$

$$\text{s.t.} \quad C1: \sum_{n\epsilon N_k^m} p_{k,n} \le p_k^{\max},\ \forall k, p_{k,n} \ge 0, \forall k, n \tag{10}$$

$$C2: \sum_{m=1}^{M} \alpha_{k,m} = 1,\ \forall k,\ \alpha_{k,m}\ \epsilon\ \{0,1\},\ \forall\ k, m \tag{11}$$

$$C3: N_k^m \bigcap N_j^m = \emptyset,\ \forall\ k \ne j,\ \forall\ m \tag{12}$$

$$C4: \left\{ n \cap \left(\bigcup_{j=1, j\ne k}^{k} N_j^m \right) = \emptyset \middle|\ n\epsilon\{n_1, n_1+1, \ldots, n_2-1, n_2\} \right\},\ \forall\ k,\ m \tag{13}$$

$$C5: \sum_{m=1}^{M} \alpha_{k,m} R_k^m \ge R_k^{\min},\ \forall\ k, \tag{14}$$

where $n_1 = \min(N_k^m)$, $n_2 = \max(N_k^m)$, and $R_k^{\min}$ shows the user's minimum data rate requirement.

Equation (9) denotes the objective function. Equations (10) and (11) denote the maximum allowed transmit power of a user and the RRH association constraint, respectively. Equations (12) and (13) denote the subchannel exclusivity and adjacency constraints, respectively, while Equation (14) shows the minimum rate requirements of user k. Table 2 contains different symbols and their description.

3 | THE PROPOSED THREE-STEP ALGORITHM

The optimization problem (9) to (14) is an MINLP problem, which jointly performs RA and RRH association. The SA constraints in Equations (12) and (13) associated with SC-FDMA results in a huge search space, and even for a fixed RRH association and PA, the optimal SA lonely is prohibitively difficult. For example, if 24 subchannels are to be assigned to 10 users for a given PA and RRH association, it will need a search across $5.26 * 10^{12}$ SAs to get the optimal solution,[41] which shows that it is prohibitively difficult to solve the problem in (9) to (14) in its existing form. Therefore, an iterative

TABLE 2 Symbols and their description

Symbols	Description
N	Total subchannels
M	Total RRHs
K	Total users
$p_k^{\max}$	Maximum allowed transmit power of a user
$\alpha_{k,m}$	RRH association matrix
$\gamma_{k,n}^m$	SNIR of kth user to RRH m on nth subchannel
σ^2	Noise power
η_k^m	EE of kth user connected to RRH m
P_T	Total energy consumption of user k
$p_{ckt,k}^m$	Circuit energy consumptions of user k connected to RRH m
p_k^s	Static power consumption of the circuit
ε	Power consumption per unit rate
$R_k^{\min}$	User's minimum rate requirements k

Abbreviations: EE, energy efficiency; RRH, remote radio head; SNIR, signal-to-interference-plus-noise ratio.

algorithm is proposed, which solves the joint SAPARA problem in (9) to (14) in three steps. The three steps of the iterative algorithms are discussed in the following sections.

3.1 | Subchannel assignment

In the first step of the presented algorithm, SA is carried out but before that we have to start the algorithm for which we supposed the initial RRH association $\boldsymbol{\alpha}^0$ such that $\boldsymbol{\alpha}^0 = \{\alpha_1^0, \alpha_2^0, ..., \alpha_K^0, \}$ and initial PA $\boldsymbol{p}^0$ such that $\boldsymbol{p}^0 = p_{k,n}^0, \ \forall\, k, \ \forall\, n$. We implement uniform PA and path-loss-based association to initialize the algorithm where $p_{k,n}^0 = (p_k^{\max}/N_k^m) : \forall k, m, n$, and $\forall k : \alpha_{k,\bar{m}}^0 = 1$ for $\bar{m} = \arg\min\ d_{k,m}$; $\alpha_{k,m}^0 = 0, \forall\ m \neq \bar{m}$. $d_{k,m}$ denotes the distance between RRH m and user k. For SA, the problem (9) to (14) can be reduced as follows:

$$\max \quad \sum_{m=1}^{M}\sum_{k=1}^{K} \alpha_{k,m}\, \eta_k^m \tag{15}$$

$$\text{s.t.} \quad N_k^m \bigcap N_j^m = \emptyset, \ \forall\ k \neq j, \ \forall\ m \tag{16}$$

$$\left\{ n \cap \left(\bigcup_{j=1, j\neq k}^{k} N_j^m \right) = \emptyset | n \epsilon \{ n_1, n_1+1, \ \ldots, n_2-1, n_2 \} \right\}, \ \forall\, k, \ m \tag{17}$$

$$\sum_{m=1}^{M} \alpha_{k,m}\, R_k^m \ \geq \ R_k^{\min}, \forall k. \tag{18}$$

At the start of iteration i, where $i \ \geq \ 1$, through solving the aforementioned problem for given $\boldsymbol{\alpha} = \boldsymbol{\alpha}^{\boldsymbol{i}}$ and $\boldsymbol{p} = \boldsymbol{p}^{\boldsymbol{i}}$, subchannels are allocated to each user, which provides N_k^m, $\forall k, m$. For SA, we present two algorithms, namely, individual SA (ISA) and subchannels block assignment (SBA) algorithms, which are explained in the following two sections.

3.1.1 | Individual subchannel allocation algorithm

The ISA algorithm is inspired from the work of Orakzai et al,[41] which performs SA among the users set associated to RRH m, which is denoted by K_m. The algorithm iteratively selects RRH m and calculates the EE of every associated user on each subchannel, and then assigns the subchannel to a user having highest EE on that subchannel. The SA is based on the sharpest rise in the EE while guaranteeing the constraints in Equations (12) and (13). That is, in each iteration, one subchannel is allocated to one user forming a best user-subchannel pair, where the SA is based on sharpest rise in the objective function. Furthermore, the algorithm inspects that whether the data rate requirement of the user in the best user-subchannel pair is attained or not. If no, then the algorithm iteratively assigns additional subchannels (one subchannel in each iteration) until the datarate requirements of the user is attained or the set of feasible subchannel empties. The pseudocode of the ISA is presented in Algorithm 1.

Algorithm 1 ISA Algorithm

1: **Initialization** K; N; M; $\widetilde{K} = \{1, \ldots, K\}$;
2: $\widetilde{N^m} = \{1, \ldots, N\}$; $\widetilde{M} = \{1, \ldots, M\}$; $N_k^m = \phi, \forall\, k \,\epsilon\, \widetilde{K}$,
3: $\forall\, m \,\epsilon\, \widetilde{M}$; $N_k^{m,f} = \widetilde{N^m}$, $\forall\, k \epsilon\, \widetilde{K}$; R_k^{min}, $\forall\, k$; $R_k^m = 0, \forall\, k,\, m$
4: **while** $\widetilde{M} \neq \phi$ **do**
5:     **while** $\widetilde{N^m} \neq \phi$ **do**
6:         $\forall\, k \epsilon \widetilde{K_m}$
7:         $\forall\, n \epsilon N_k^{m,f} \,\cup\, \widetilde{N}$
8:         $\eta_k^m = f(\eta_k)$, $N_k^m \cup n$
9:         $k^*,\ n^* = \arg\ \max_{k,n}\ \eta_k^m$
10:         $N_{k^*}^m = N_{k^*}^m \cup n^*$
11:         $\widetilde{N^m} \setminus n^*$
12:         $N_k^{m,f} = \{\min\left(N_{k^*}^m\right) - 1,\ \max\left(N_{k^*}^m\right) + 1\} \,\cap\, \widetilde{N^m}$
13:         $R_{k^*}^m = W \left|N_k^m\right| \log_2\left(1 + \frac{1}{\left|N_{k^*}^m\right|} \sum_{n \,\epsilon\, N_{k^*}^m} \left(\frac{p_{k^*,n} \left|h_{k^*,n}^m\right|^2}{\sigma^2 + I_{k^*,n}^m} \right)\right)$
14:         **while** $\left(R_{k^*}^m < R_{k^*}^{min}\ and\ N_{k^*}^{m,f} \neq \phi\right)$ **do**
15:             $\triangle\eta_{k^*}^m = f\left(\eta_{k^*},\ N_{k^*}^m \cup n\right) - f\left(\eta_{k^*},\ N_{k^*}^m\right),\ \forall\, n \epsilon N_{k^*}^{m,f}$
16:             $n^* = \arg\ \max_{n \,\epsilon\, N_{k^*}^{m,f}}\ \triangle\eta_{k^*}^m$
17:             Repeat steps 10 to 13
18:         **end while**
19:         $\widetilde{K} \setminus k^*$
20:     **end while**
21:     $\widetilde{M} \setminus m$
22: **end while**

The algorithm is initialized in lines 1 to 3 where N_k^m denotes the subchannels set presently allocated to kth user associated to RRH m and $N_k^{m,f}$ denotes the feasible subchannels set for kth user associated to RRH m. Initially, as the currently assigned subchannels set of kth user connected to RRH m is empty and all the subchannels are available, therefore $N_k^m = \phi$ and $N_k^{mf} = N$. After initializing, the algorithm selects a subchannel and assigns it to a user k, which achieves maximum EE on this subchannel (lines 8 and 9). This user and subchannel pair is denoted by (k^* *and* n^*). After assigning subchannel n^* to k^*, $N_{k^*}^m$ and $N_{k^*}^{m,f}$ are updated (lines 10 to 12). After this, line 13 computes the attainable rate of that user on its updated set of assigned subchannels. Lines 14 to 18 assign an extra subchannel to this user from the set of its feasible subchannels until its minimum rate requirement is fulfilled or its set of feasible subchannels goes empty. In these lines, first, the increase in the EE represented by $\triangle\eta_{k^*}^m$ is calculated for each additional subchannel $n \,\epsilon\, N_k^m$ (line 15), which shows the difference between the EEs of user k^* when the subchannel n is added to its allocated subchannel set (i.e, $f(\eta_{k^*},\ N_{k^*}^m \cup n)$) and its EE without the addition of subchannel n (i.e, $f(\eta_{k^*},\ N_{k^*}^m)$). The most beneficial subchannel in terms of EE is picked in line 16. In line 17, the operations in lines 10 to 13 are repeated to update N_k^m, $N_k^{m,f}$, and $R_{k^*}^m$. Line 19 updates the users having no subchannel. The algorithm is repeated until $\widetilde{M}$ is empty (lines 5 to 21).

3.1.2 | Subchannels block allocation algorithm

In SBA algorithm, the set of available subchannels N is divided into K_m groups having contiguous subchannels where K_m is the set of users connected to RRH m. Unlike the ISA algorithm, for every RRH m, the achievable EE of every user k on each subchannel group is computed iteratively, and then the subchannels group is assigned to the user who achieved the highest EE on this group. This way, the user and subchannel group pair is identified. In the next iteration, the user and subchannel group pair identified in the first iteration will not be considered for subchannel group assignment and the achievable EE of every remaining user is computed on immediate next subchannels, group and subchannel group assigning is performed based on the highest achieved EE as in the previous iteration. This way, the entire subchannels groups are allocated to the users.

3.2 | Power allocation algorithm

After SA in the first step, PA to the assigned subchannels is carried out in this step for which the optimization problem in (9) to (14) reduces as follows:

$$\max \quad \sum_{m=1}^{M} \sum_{k=1}^{K} \alpha_{k,m}\, \eta_k^m \tag{19}$$

$$\text{s.t.} \quad \sum_{n \epsilon N_k^m} p_{k,n} \le p_k^{\max},\ \forall\, k,\ p_{k,n} \ge 0,\ \forall\, k, n. \tag{20}$$

For given $\boldsymbol{\alpha} = \boldsymbol{\alpha}^{\boldsymbol{i}}$ and attained N_k^m in the first step, PA to N_k^m is performed by (1) equal power distribution (EPD) and (2) interior point algorithm (IPA). The EPD uniformly distributes the maximum transmit power of kth user connected to RRH m among all its assigned subchannels. The EPD can be expressed as follows:

$$p_{k,n} = p_k^{\max} / \left|N_k^m\right|, \quad \forall\, k, n, m. \tag{21}$$

On the other hand, IPA or barrier method is utilized for near-optimal PA. After SA and PA, we take the achieved solution as p^{i+1}.

3.3 | RRH association

RRH association is carried out with obtained SA and PA. After obtaining SA in the first step and PA in second step, problem (9) to (14) reduces to the following RRH association problem:

$$\max \quad \sum_{m=1}^{M} \sum_{k=1}^{K} \alpha_{k,m}\, \eta_k^m \tag{22}$$

$$\textbf{s. t.} \sum_{m=1}^{M} \alpha_{k,m} = 1,\ \forall\, k,\ \alpha_{k,m}\, \epsilon\, \{0,1\},\ \forall\, k, m. \tag{23}$$

The problem in Equations (22) and (23) is solved by taking all $\alpha_{k,m}$ equal to zeros, except that $\alpha_{k,\bar{\bar{m}}=1}$, where $\bar{\bar{m}}$ can be expressed as follows:

$$\bar{\bar{m}} = \arg\ \max \left(R_{k,n}(m)\right), \tag{24}$$

where $R_{k,n}(m)$ denotes the rate of kth user to RRH m on nth subchannel and can be represented as follows:

$$R_k^m = W \left|N_k^m\right| \log_2 \left(1 + \frac{1}{\left|N_k^m\right|} \sum_{n\, \epsilon\, N_k} \left(\gamma_{k,n}^m\right)\right). \tag{25}$$

The RRH association problem in Equations (22) and (23) is solved by integer relaxation method.[43] The proposed algorithm associates user k with the RRH, which gives highest benefit to user k in terms of EE. We denote this solution by α^{i+1}, and then $(i + 1)$th iteration starts. The three-step iterative algorithms are repeated until convergence.

To analyze the complexity of our proposed algorithm, the complete iterations of the middle while loop and inner most while loop in Algorithm 1 are considered. The algorithm's steps 5 to 20 that involve the middle and innermost while loops will run for each individual RRH, and therefore, these steps will be executed M times. The complexity of the algorithm for each RRH mainly depends upon steps 8 and 15 in which η_k^m and $\triangle\eta_{k^*}^m$ are computed, respectively. The first complete iteration of the middle while loop will need $\mathcal{O}(NK)$ executions for the calculation of η_k^m. This complexity decreases for the subsequent iterations because the number of users and subchannels will be less than K and N, respectively, while the first complete iteration of the inner most while loop will need $\mathcal{O}(|N_k^f|)$ operations for the computation of $\triangle\eta_{k^*}^m$. Its worst-case complexity will be $\mathcal{O}((N-1)|N_k^f|)$. The first complete iteration of the middle while loop will need $\mathcal{O}(NK)$ operations for the computation of η_k^m. This complexity decreases for the subsequent iterations because the number of users and subchannels will be less than K and N, respectively, while the first complete iteration of the inner most while loop will need $\mathcal{O}(|N_k^f|)$ operations for the computation of $\triangle\eta_{k^*}^m$. Its worst-case complexity will be $\mathcal{O}((N-1)|N_k^f|)$. This complexity decreases for the subsequent iterations of the inner most while loop because the number of the subchannels will be less than $(N - 1)$. Because there are N middle iterations, which will run for M number of times, the algorithm's worst-case complexity cannot exceed $\mathcal{O}(M(N(NK + (N-1)|N_k^f|))) \approx \mathcal{O}(MN^2K)$.

4 | RESULTS AND DISCUSSIONS

We assume a multitier H-CRAN in the UL, which comprises of a macrocell RRH with a coverage radius of r meters, two picocell RRHs denoted by P1-RRH and P2-RRH, and two femtocell-RRHs denoted by F1-RRH and F2-RRH, as illustrated in Figure 2. Furthermore, the system bandwidth B is split into N subchannels, each having W bandwidth. There are K users, which are deployed randomly. The channel gain comprises of two components, ie, a large-scale path-loss component calculated by Cost-Hata model[44] and a small-scale Rayleigh fast-fading component. The spectral density of noise power is −174 dBm/Hz. We evaluate the performance of our presented algorithms for various parameters, ie, $R_k^{\min}, r, K, N, P_k^{\max}, P^s, \epsilon$, and ζ.

The performances of our proposed ISA-based suboptimal PA and RRH association (ISA-SOPARA), and SBA-based suboptimal PA and RRH association (SBA-SOPARA) algorithms have been compared with low complexity equal power and equal subchannel (EPES) allocation and a high complexity baseline algorithms. In EPES algorithm, the subchannels of a RRH are equally divided into its associated users, the maximum allowed power of a user is uniformly distributed among its assign subchannel, and a distance-based RRH association is performed. While, in our considered base-line algorithm, branch and bound method is used to perform RRH association and SA, and IPA is used for PA. Our formulated joint SAPARA problem is an MINLP problem, which is generally NP-hard and cannot be solved in its existing form. Therefore, despite the high complexity of branch and bound method and IPA, we used them as base line for comparison, because they provide near-optimal results.

To compare our presented algorithms with EPES and baseline algorithms in terms of EE performance, we plot the EE versus different values of $p_k^{\max}$, N, and K in Figures 3 to 5, respectively. For Figure 3, K and N are kept constant. For Figure 4, K and maximum transmit power are kept constany, while for Figure 5, N and maximum transmit powers are kept constant. Furthermore, $R_k^{\min}$ is set as 200 Kbps for all the three combinations. It is clear from Figure 3 that the EE decreases with rise in maximum transmit power of the users. Figure 4 shows that, despite the increase in the complexity of the algorithms, increase in the number of subchannels does not bring considerable change in the EE performance of the algorithm, whereas Figure 5 illustrates that an increase in the number of users increases the EE. In addition, it is clear from the three figures, ie, Figures 3 to 5, that our proposed algorithms are near in performance to the baseline algorithm while they outperform the EPES algorithm in terms of EE.

Figures 6 and 7 demonstrate the network sum rate and EE performances of our proposed ISA-based optimal power allocation (ISA-SOPARA) and SBA-based optimal power allocation (SBA-SOPARA) algorithms for different cell radii of

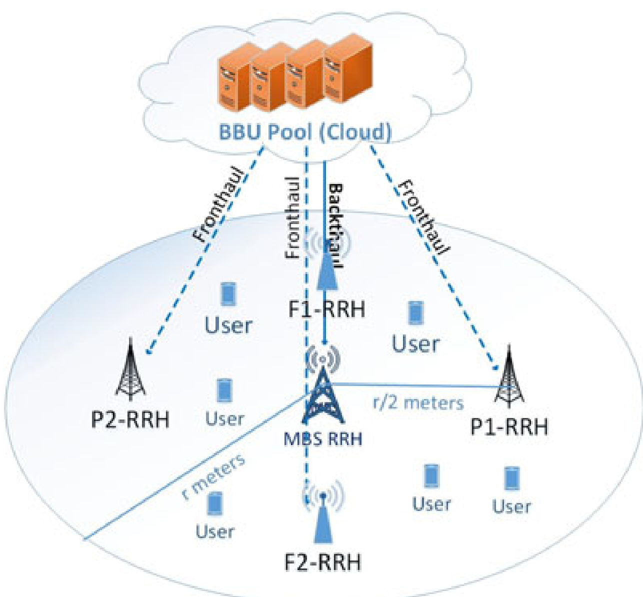

FIGURE 2 Simulations scenario. BBU, base band unit

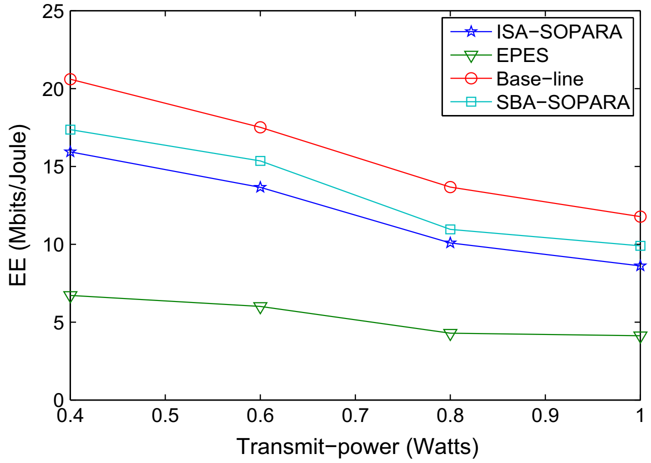

FIGURE 3 Energy efficiency (EE) versus transmit power for $K = 5$, $N = 10$. EPES, equal power and equal subchannel; ISA-SOPARA, individual subchannel assignment–based suboptimal power allocation and remote radio head association; SBA-SOPARA, subchannels block assignment–based suboptimal power allocation and remote radio head association

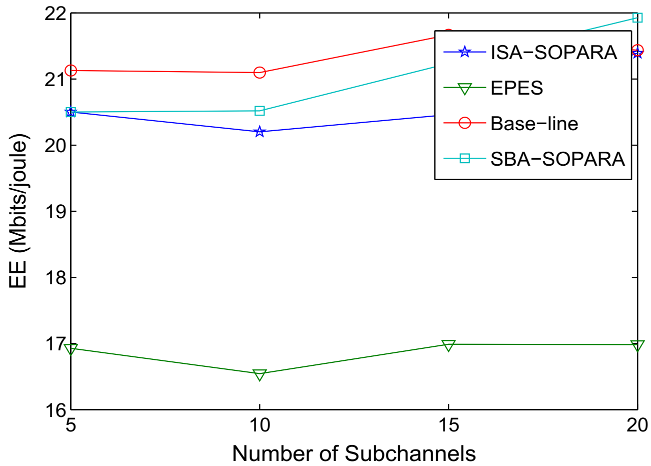

FIGURE 4 Energy efficiency (EE) versus number of subchannels for $K = 5$ and $p_u^{\max} = 0.4$. EPES, equal power and equal subchannel; ISA-SOPARA, individual subchannel assignment–based suboptimal power allocation and remote radio head association; SBA-SOPARA, subchannels block assignment–based suboptimal power allocation and remote radio head association

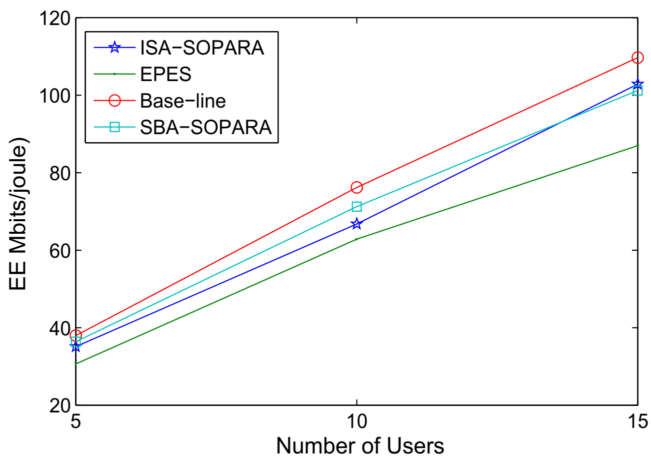

FIGURE 5 Energy efficiency (EE) versus number of users for $p_u^{\max} = 0.4$ and $N = 20$

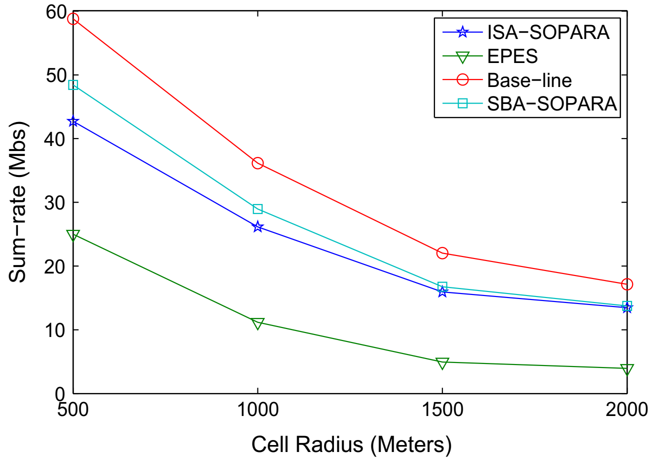

FIGURE 6 Network sum rate evaluation and comparison of the proposed algorithms with equal power and equal subchannel (EPES) and baseline algorithms for different cell radii. ISA-SOPARA, individual subchannel assignment–based suboptimal power allocation and remote radio head association; SBA-SOPARA, subchannels block assignment–based suboptimal power allocation and remote radio head association

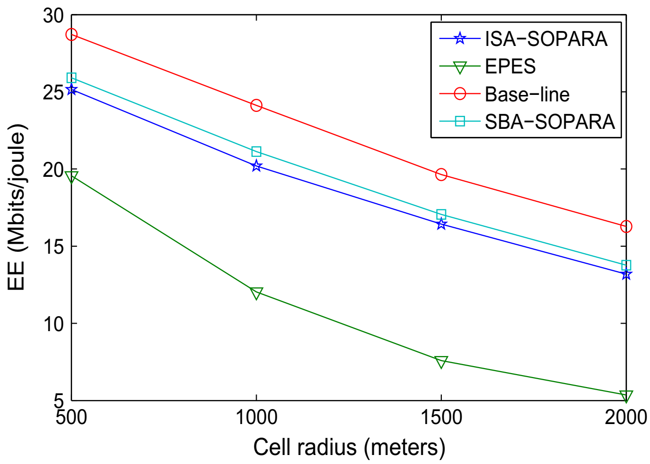

FIGURE 7 Energy efficiency (EE) performance evaluation and comparison of the proposed algorithms with equal power and equal subchannel (EPES) and baseline algorithms for different cell radii. ISA-SOPARA, individual subchannel assignment–based suboptimal power allocation and remote radio head association; SBA-SOPARA, subchannels block assignment–based suboptimal power allocation and remote radio head association

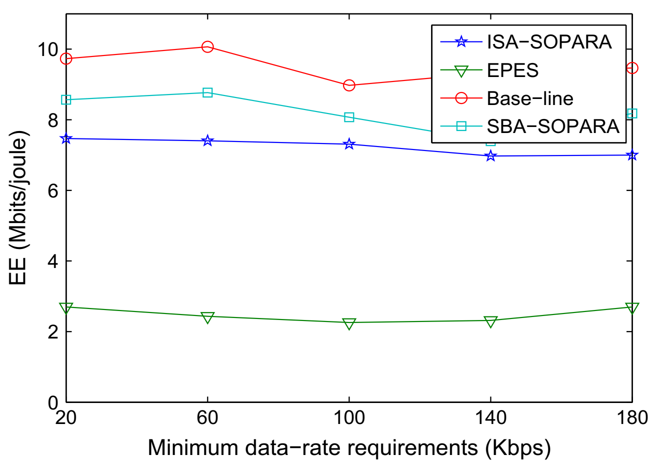

FIGURE 8 Energy efficiency (EE) versus different values of user's minimum data rate requirements. EPES, equal power and equal subchannel; ISA-SOPARA, individual subchannel assignment–based suboptimal power allocation and remote radio head association; SBA-SOPARA, subchannels block assignment–based suboptimal power allocation and remote radio head association

the macrocell, respectively, and compare them with the EPES and baseline algorithms. The $R_k^{\min}$, $p_k^{\max}$, N, and K are kept constant. The figures show that, as the cell radius of the macrocell increases, the network sum rate and EE decrease. This is due to the fact that, the larger the distance between a user and its RRH, the more will be drop in the signal strength and data rate. Thus, the EE will also be lowered because of its direct proportion to the data rate. The figures show that both our algorithms (ie, ISA-SOPARA and SBA-SOPARA) perform better than EPES algorithm in terms of network sum rate as well as EE while the proposed algorithms are close in performance with the baseline algorithm.

We next evaluate the EE performances of our proposed algorithms for various values of $R_k^{\min}$. For simplicity, we suppose that all users have the same minimum data rate requirements. Furthermore, different $R_k^{\min}$ taken are 20 kbps, 40 kbps, 100 kbps, 140 kbps, and 180 kbps. The results for EE are plotted in Figure 8, which shows that the EE performance of the proposed ISA-SOPARA and SBA-SOPARA algorithms is much better than the EPES allocation algorithm. The figure also demonstrates that the ISA-SOPARA and SBA-SOPARA algorithms are near to the baseline algorithm in terms of EE performances; therefore, these algorithms can be adapted for systems having limited computational resources.

Figures 9 to 11 show the EE performance of our proposed algorithms against different values of amplifier drain efficiency ζ, the static circuit power P^s, and the dynamic power per unit data rate ϵ, respectively. It is clear from the three

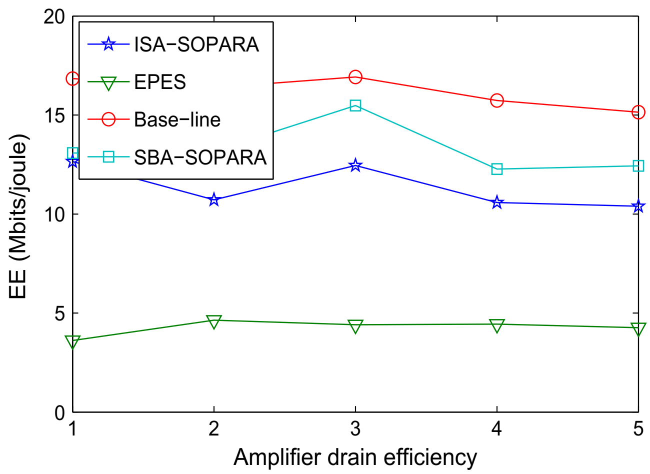

FIGURE 9 Energy efficiency (EE) performance evaluation of individual subchannel assignment–based suboptimal power allocation and remote radio head association (ISA-SOPARA) and subchannels block assignment–based suboptimal power allocation and remote radio head association (SBA-SOPARA) and their comparison with equal power and equal subchannel (EPES) and baseline algorithms against different values of amplifier drain efficiency ζ for $R_k^{\min} = 60$ Kbits/ sec, $r = 500\ m$, $K = 10$, $N = 20$, $P_k^{\max} = 0.4$ watts, $P_k^{ckt} = 0.05$, and $\epsilon = 0.4$

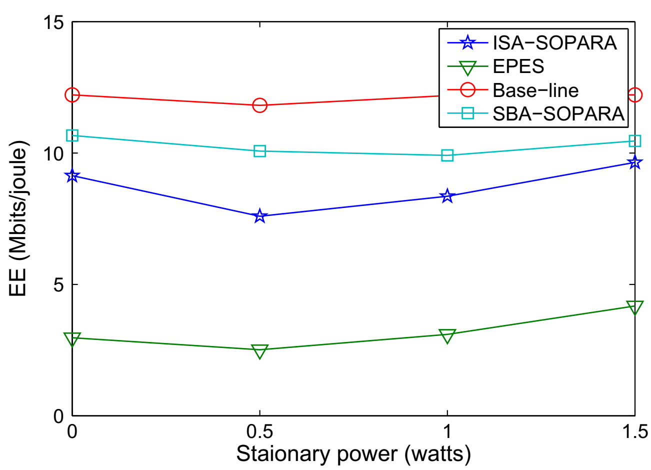

FIGURE 10 Energy efficiency (EE) evaluation against different values of P^s with keeping other parameters fixed, eg, $R_k^{\min} = 60$ Kbits/ sec, $r = 500\ m$, $K = 10$, $N = 20$, $\epsilon = 0.4$, and $P_k^{\max} = 0.4$ watts. EPES, equal power and equal subchannel; ISA-SOPARA, individual subchannel assignment–based suboptimal power allocation and remote radio head association; SBA-SOPARA, subchannels block assignment–based suboptimal power allocation and remote radio head association

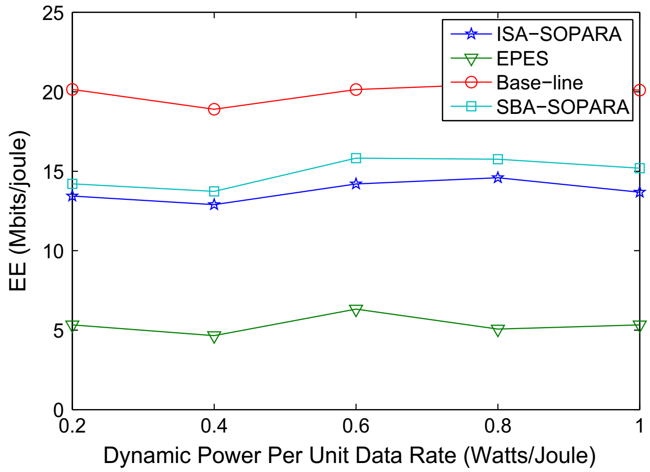

FIGURE 11 Energy efficiency (EE) evaluation against different values of ϵ with keeping other parameters fixed. EPES, equal power and equal subchannel; ISA-SOPARA, individual subchannel assignment–based suboptimal power allocation and remote radio head association; SBA-SOPARA, subchannels block assignment–based suboptimal power allocation and remote radio head association

figures, ie, Figures 9 to 11, that our proposed algorithms (ISA-based suboptimal PA and RRH association and SBA-based suboptimal PA and RRH association) perform better than the EPES algorithm while they are near in performance to the baseline algorithm in terms of EE.

5 | CONCLUSION

In this paper, a joint SA, PA and RRH association problem has been formulated for a SC-FDMA-based multitier H-CRANs. The energy efficiency maximization is considered as the objective subject to transmit power budget, minimum data rate requirements, subchannel exclusivity, and adjacency constraints. The formulated problem is an MINLP, which is prohibitively difficult to solve. Therefore, a three-step iterative algorithm is developed to solve the MINLP where, in the first step, subchannels are assigned to users; in the second step, the power is allocated to all the subchannels assigned to each user in the first step, while in the third step, the RRH association is updated. Simulation results have revealed the significance of the presented algorithms.

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REFERENCES

1. Cisco. *Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2015–2020*. White paper. 2016.
2. ICT Data and Statistics Division. *The World in 2015: ICT Facts and Figures*. Geneva, Switzerland: International Telecommunication Union. 2015.
3. Li Y, Qian M, Jin D, Hui P, Wang Z, Chen S. Multiple mobile data offloading through disruption tolerant networks. *IEEE Trans Mob Comput*. 2014;13(7):1579-96.
4. Wang L, Wang Y, Ding Z, Wang X. Cell selection game for densely-deployed sensor and mobile devices in 5G networks integrating heterogeneous cells and the Internet of Things. *Sensors*. 2015;15(9):24230-24256.
5. Cheng W, Zhang X, Zhang H. Heterogeneous statistical QoS provisioning over 5G wireless full-duplex networks. Paper presented at: 2015 IEEE Conference on Computer Communications (INFOCOM); 2015; Kowloon, Hong Kong.
6. Cai S, Che Y, Duan L, Wang J, Zhou S, Zhang R. Green 5G heterogeneous networks through dynamic small-cell operation. *IEEE J Sel Areas Commun*. 2016;34(5):1103-115.
7. Chih-Lin I, Rowell C, Han S, Xu Z, Li G, Pan Z. Toward green and soft: a 5G perspective. *IEEE Commun Mag*. 2014;52(2):66-73.
8. Checko A, Christiansen HL, Yan Y, et al. Cloud RAN for mobile networks-a technology overview. *IEEE Commun Surv Tutor*. 2015;17(1):405-426.
9. Peng M, Li Y, Jiang J, Li J, Wang C. Heterogeneous cloud radio access networks: a new perspective for enhancing spectral and energy efficiencies. *IEEE Wirel Commun*. 2014;21(6):126-135.

10. Rico-Alvarino A, Vajapeyam M, Xu H, et al. An overview of 3GPP enhancements on machine to machine communications. *IEEE Commun Mag*. 2016;54(6):14-21.
11. Ruby R, Leung VC, Michelson DG. Uplink scheduler for SC-FDMA-based heterogeneous traffic networks with QoS assurance and guaranteed resource utilization. *IEEE Trans Veh Technol*. 2015;64(10):4780-4796.
12. Tombaz S, Sung KW, Zander J. Impact of densification on energy efficiency in wireless access networks. Paper presented at: 2012 IEEE Globecom Workshops; 2012; Anaheim, CA.
13. Wong IC, Evans BL. Optimal downlink OFDMA resource allocation with linear complexity to maximize ergodic rates. *IEEE Trans Wirel Commun*. 2008;7(3):962-71.
14. Fei Z, Xing C, Li N, Kuang J. Adaptive multiobjective optimisation for energy efficient interference coordination in multicell networks. *IET Commun*. 2014;8(8):1374-1383.
15. Song L, Chai KK, Chen Y, Schormans J, Loo J, Vinel A. Qos-aware energy-efficient cooperative scheme for cluster-based IoT systems. *IEEE Syst J*. 2017;11(3):1447-1455.
16. Sun C, Cen Y, Yang C. Energy efficient OFDM relay systems. *IEEE Trans Commun*. 2013;61(5):1797-1809.
17. Wang Y, Xu W, Yang K, Lin J. Optimal energy-efficient power allocation for OFDM-based cognitive radio networks. *IEEE Commun Lett*. 2012;16(9):1420-1423.
18. Dechene DJ, Shami A. Energy-aware resource allocation strategies for LTE uplink with synchronous HARQ constraints. *IEEE Trans Mob Comput*. 2014;13(2):422-433.
19. Ruder MA, Wechsler J, Gerstacker WH. User pairing and power allocation for energy efficient SC-FDMA transmission with QoS requirements. Paper presented at: 2013 IEEE Globecom Workshops (GC Wkshps); 2013; Atlanta, GA.
20. Kalil M, Shami A, Al-Dweik A. Qos-aware power-efficient scheduler for LTE uplink. *IEEE Trans Mob Comput*. 2015;14(8):1672-1685.
21. Ahmad A, Assaad M. Power efficient resource allocation in uplink SC-FDMA systems. Paper presented at: 2011 IEEE 22nd International Symposium on Personal, Indoor and Mobile Radio Communications; 2011; Toronto, Canada.
22. Ahmad A. Resource allocation and adaptive modulation in uplink SC-FDMA systems. *Wirel Pers Commun*. 2014;75(4):2217-2242.
23. Ahmad A, Khan MTR, Kaleem Z. Uplink optimal power allocation for heterogeneous multiuser SIMO SC-FDMA networks. *Electron Lett*. 2016;52(24):1990-1992.
24. Ahmad A. Power allocation for uplink SC-FDMA systems with arbitrary input distribution. *Electron Lett*. 2015;52(2):111-113.
25. Tsiropoulou EE, Kapoukakis A, Papavassiliou S. Energy-efficient subcarrier allocation in SC-FDMA wireless networks based on multilateral model of bargaining. Paper presented at: 2013 IFIP Networking Conference; 2013; Brooklyn, NY.
26. Aijaz A, Chu X, Aghvami AH. Energy efficient design of SC-FDMA based uplink under QoS constraints. *IEEE Wirel Commun Lett*. 2014;3(2):149-152.
27. Triantafyllopoulou D, Kollias K, Moessner K. QoS and energy efficient resource allocation in uplink SC-FDMA systems. *IEEE Trans Wirel Commun*. 2015;14(6):3033-3045.
28. Zheng Z, Ji Q, Dan L, Li S. Energy-efficient power allocation for uplink SC-FDMA. Paper presented at: 2012 8th International Conference on Wireless Communications, Networking and Mobile Computing; 2012; Shanghai, China.
29. Shi Y, Zhang J, Letaief KB. Group sparse beamforming for green Cloud-RAN. *IEEE Trans Wirel Commun*. 2014;13(5):2809-2823.
30. Huang X, Xue G, Yu R, Leng S. Joint scheduling and beamforming coordination in cloud radio access networks with QoS guarantees. *IEEE Trans Veh Technol*. 2016;65(7):5449-5460.
31. Yoon C, Cho D-H. Energy efficient beamforming and power allocation in dynamic TDD based C-RAN system. *IEEE Commun Lett*. 2015;19(10):1806-1809.
32. Luo S, Zhang R, Lim TJ. Downlink and uplink energy minimization through user association and beamforming in C-RAN. *IEEE Trans Wirel Commun*. 2015;14(1):494-508.
33. Tang J, Tay WP, Quek TQ. Cross-layer resource allocation with elastic service scaling in cloud radio access network. *IEEE Trans Wirel Commun*. 2015;14(9):5068-5081.
34. Tran GK, Shimodaira H, Rezagah RE, Sakaguchi K, Araki K. Dynamic cell activation and user association for green 5G heterogeneous cellular networks. Paper presented at: 2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC); 2015; Hong Kong, China.
35. Peng M, Zhang K, Jiang J, Wang J, Wang W. Energy-efficient resource assignment and power allocation in heterogeneous cloud radio access networks. *IEEE Trans Veh Technol*. 2015;64(11):5275-5287.
36. Tran HQ, Truong PQ, Phan CV, Vien Q-T. On the energy efficiency of NOMA for wireless backhaul in multi-tier heterogeneous CRAN; 2017; Da Nang, Vietnam.
37. Wang K, Zhou W, Mao S. On joint BBU/RRH resource allocation in heterogeneous Cloud-RANs. *IEEE Internet Things J*. 2017;4(3):749-759.
38. Li J, Peng M, Yu Y, Ding Z. Energy-efficient joint congestion control and resource optimization in heterogeneous cloud radio access networks. *IEEE Trans Veh Technol*. 2016;65(12):9873-9887.
39. Ali M, Rabbani Q, Naeem M, Qaisar S, Qamar F. Joint user association, power allocation, and throughput maximization in 5G H-CRAN networks. *IEEE Trans Veh Technol*. 2017;66(10):9254-9262.
40. Ali S, Ahmad A, Iqbal R, Saleem S, Umer T. Joint RRH-association, sub-channel assignment and power allocation in multi-tier 5G C-Rans. *IEEE Access*. 2018;6:34393-34402.
41. Orakzai FA, Ahmad A, Khan MT, Iqbal M. Optimal energy-efficient resource allocation in uplink SC-FDMA networks. *Trans Emerg Telecommun Technol*. 2017;28(8):1.

42. Cui S, Goldsmith AJ, Bahai A. Energy-efficiency of MIMO and cooperative MIMO techniques in sensor networks. *IEEE J Sel Areas Commun*. 2004;22(6):1089-1098.
43. Hao W, Zeng M, Chu Z, Yang S, Sun G. Energy-efficient resource allocation for mmWave massive MIMO HetNets with wireless backhaul. *IEEE Access*. 2017;6:2457-2471.
44. Nisirat MA, Ismail M, Nissirat L, AlKhawaldeh S. Is Hata path loss model a macro-cell model only? a question of debate. Paper presented at: 2012 International Conference on Computer and Communication Engineering (ICCCE); 2012; Kuala Lumpur, Malaysia.

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