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5G Software-Defined Heterogeneous Networks With Cooperation and Partial Connectivity

TAO HAN[1], (Member, IEEE), SHIMIN LI[1], YI ZHONG[1], (Member, IEEE), ZHIQUAN BAI[2], (Member, IEEE), AND KYUNG-SUP KWAK[3], (Member, IEEE)

[1]School of Electronic Information and Communications, Huazhong University of Science and Technology, Wuhan 430074, China
[2]School of Information Science and Engineering, Shandong University, Jinan 250100, China
[3]School of Electrical and Computer Engineering, Inha University, Incheon 402-751, South Korea

Corresponding author: Yi Zhong (yzhong@hust.edu.cn)

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ABSTRACT The heterogeneous network composed of small cell base stations (SCBSs) and macro base stations (MBSs) has been widely deployed to alleviate the load of conventional MBSs, which may also cause severe interference and large energy consumption. The existing literature generally focus on the heterogeneous networks either without cooperation or with cross-tier cooperation. In this paper, we introduce a central controller and mobile edge cloud (MEC) servers and propose a heterogeneous network with SCBSs cooperation, i.e., the intra-tier cooperation. A novel load balancing metric instead of the simple access probability ratio is introduced. Based on the utility theory, we comprehensively evaluate several important performance metrics such as connectivity probability, load balancing, and energy efficiency to optimize the overall performance of the network. Moreover, in the special case of allowing partial connectivity, the discrete stochastic optimization algorithm is proposed so that the software-defined networks (SDNs) controller can adjust network parameters with the help of MEC servers to maximize the overall energy efficiency. The simulation results demonstrate that our proposed approach is valid to optimize the network in accordance with the user requirements. This paper provides a useful reference for the practical deployment of software-defined heterogeneous networks where the energy efficiency is increasingly becoming a key concern.

INDEX TERMS Heterogeneous networks, software-defined networks, cooperative communication, utility theory, partial connectivity, discrete stochastic optimization algorithm.

I. INTRODUCTION

A. MOTIVATIONS

Mobile communication technology is developing rapidly in recent decades, and the number of mobile users is also increasing dramatically. It shows that the wireless traffic will increase by more than 500 times from 2010 to 2020 [1]. The fifth-generation (5G) mobile communication system requires greater system capacity, higher transmission rate, higher energy efficiency, lower latency, and lower system cost [2], [3]. However, traditional cellular networks consisting of macro base stations (MBSs) are insufficient to meet these requirements. Thus, the small cell base stations (SCBSs) are deployed in the traditional cellular networks, forming the heterogeneous cellular networks [4]. The SCBSs show great potential due to the benefits of small coverage, low power, low cost, and flexible deployment [5], [6]. In the heterogeneous networks, the SCBSs can reduce the load of MBSs by offloading users from the congested MBSs, thereby providing a better service experience for users [7].

Considerable researches exist on analyzing the performance of general heterogeneous networks. Dhillon et al. proposed a tractable model for K-tier heterogeneous networks and derive the coverage probability [8]. In [9], the coverage and the energy efficiency are analyzed in multi-tier 5G heterogeneous small cell networks. Nevertheless, the challenges such as large interference and high energy consumption still exist in the heterogeneous networks. In-depth studies are still required to further improve the overall performance of the heterogeneous networks.

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Most existing studies focused on the individual performance metric of heterogeneous networks in non-cooperative or cross-cooperative scenarios [10], [11]. However, few of them have taken multiple performance metrics comprehensively into account to improve the overall performance of the network. In this paper, we propose a novel heterogeneous network scheme to improve the overall system performance (such as connectivity probability, load balancing and energy efficiency) with intra-tier cooperation. We derive the load balancing and the energy efficiency based on the proposed load balancing metric and BS power consumption model. Moreover, most existing works use the SDN controller to control and manage the network [12]. We propose to additionally use MEC servers to implement the local management to make the decisions much more timely. Furthermore, the discrete stochastic optimization algorithm is proposed to improve the energy efficiency of the network with partial connectivity.

B. RELATED WORKS

Due to the coexistence of multi-tier BSs and the dense deployment of SCBSs, the performance of the heterogeneous networks is limited to the severe interference, including intra-tier interference and cross-tier interference. Gesbert et al. prove that in an interference-limited dense network, multi-cell cooperation allows the user data to be co-processed by multiple BSs [13]. It can mitigate or utilize the interference and significantly improve the network performance, especially the coverage performance. Tanbourgi et al. consider that the users always select the cooperative BSs by the distance and derive the expressions of signal to interference and noise ratio (SINR) [14]. The work in [15] extends [14] and analyzes the coverage probability in the multi-tier heterogeneous networks. In the model proposed by Nigam *et al.* [16], the user simultaneously connects to several cooperative BSs with the strongest received power with cross-tier cooperation, and the simulation results indicate that the cooperation increases the coverage probability of general users and cell-edge users by 17% and 24% respectively when compared with the non-cooperative case. All these studies show that the cooperation can improve the coverage performance of networks. However, the performance of the intra-tier cooperation in heterogeneous networks has not been explored.

Achieving low energy consumption and high energy efficiency of wireless communication systems is a main goal of the design of the next generation of wireless networks. It is reported that the energy consumption of the information technology industry accounts for 10% of the total global energy consumption, where the proportion of energy consumption generated by wireless communication cannot be underestimated [17]. The goal of the EARTH project is to reduce the energy consumption of mobile broadband networks by 50% [18]. Razavi and Clausse [19] demonstrate that the energy consumption has increased significantly by introducing the SCBS tier. The sleeping strategy is an effective way to save energy, but it cannot necessarily improve the energy efficiency for the reason that the energy efficiency is affected by both throughput and energy consumption [20]. In [21], all BSs have four different operating states, namely transmit, ready, listen, and sleep, where the BSs can adjust their operating states according to the QoS requirements, thereby reducing the energy consumption of the network. Besides, Hekmat and Mieghem [22] indicate that a network allowing part of nodes to be disconnected consumes much lower energy than a network with all nodes connected. In the actual scenario, not all nodes always need to be connected, i.e., partial connectivity is allowed [23]. It is well known that the massive Machine Type Communications (mMTC), which is one of the three major application scenarios of 5G, requires low transmission rate and is insensitive to delay, which means allowing partial connectivity [24], [25]. Therefore, we explore the approach to optimize the energy efficiency in the scenario that allows partial connectivity.

The density of BSs is a pivotal factor affecting the performance of wireless networks [26], which also has a crucial impact on the performance of heterogeneous networks with dense SCBSs, especially for energy efficiency [27]. Ge *et al.* [28] study the relationship between the density of SCBSs and energy efficiency, and draw a conclusion that there is a density limit of SCBSs in ultra-dense cellular networks, but it does not give the method to solve the density limit. Cao *et al.* [29] determine the optimal BS density for homogeneous networks and heterogeneous networks to minimize network energy consumption. In order to optimize the energy efficiency of the two-tier heterogeneous network in a non-cooperative scenario, the best BS density ratio is obtained in [30]. The effort of the spatial and temporal fluctuation of the traffic on the performance of the heterogeneous cellular networks is explored in [31] and [32].

The fusion of multiple technologies is the trend of the technological development. SDN has been widely used in the wired networks [33]. In order to achieve efficient management and control of wireless networks, many researchers have tried to integrate SDN with wireless networks [34], [35]. An approximate SDN structure applied to wireless networks - SDWN is proposed in [36]. In order to combine the advantages of cellular networks and WLANs, Zhang *et al.* [37] design a unified wireless network structure named as SDN-UWN and elaborate the design of the controller and network nodes. [38] and [39] utilize SDN to improve the efficiency and overall QoS of heterogeneous networks respectively. In addition, Spapis *et al.* [40] propose a complex wireless access cooperation scheme - SoftMobile in heterogeneous networks based on SDN. Furthermore, an intelligent scheme for cellular networks - SDHCN is proposed in [41] to improve the overall performance of the network by adjusting the bias factor values of multi-tier BSs. As a consequence, integrating SDN into the heterogeneous cellular networks is promising to make the network management facile.

Network synchronization is a key function in wireless network, which can support data fusion, geolocation, target tracking and other services [42], [45]. In order to provide these services in a cooperative fashion, the cooperative

BSs need to share a common clock, which requires efficient synchronization technology to implement. Vaghefi and Buehrer [43] and Etzlinger *et al.* [44] respectively put forward the semidefinite programming (SDP) relaxation method and the sequential belief propagation (BP) algorithm to achieve cooperative synchronization and localization, which can be effectively applied to cooperative networks. Xiong *et al.* [45] propose a framework for cooperative network synchronization analysis and derive closed-form asymptotic expressions under performance limits, which is demonstrated to be applicable to practical wireless networks through results. These studies show that there are efficient network synchronization techniques and algorithms suitable for cooperative networks, and can bring significant improvement in robustness, efficiency and other performance.

C. CONTRIBUTIONS

The main contributions of this paper are summarized as follows:

- We propose to integrate a central controller and multiple MEC servers to establish a heterogeneous network with the intra-tier cooperation. Each user choose either a single MBS or an SCBS cooperative group that provides the highest received signal strength (RSS) as its serving BS/BSs. The simulation results demonstrate that the connectivity probability of the intra-tier cooperation is better than that of the cross-tier cooperation in the heterogeneous network with dense SCBSs.
- A novel load balancing metric as well as a BS power consumption model considering the number of users are proposed to analyze the load balancing and the energy efficiency of the heterogeneous networks. Based on the utility theory, we formulate an overall performance optimization problem of the network. Through the exhaustive search algorithm, we obtain the optimal density ratio of BSs in two tiers that makes the network reach an optimal state, i.e., simultaneously achieving balanced load, high connectivity probability and high energy efficiency.
- In the special case of partial connectivity, we propose the discrete stochastic optimization algorithm that the central controller sends proper instructions to the MEC servers to adjust the transmit power and the operating mode of SCBSs, thus maximizing the network energy efficiency. The proposed approach can optimize the network in accordance with the actual requirements of users.

The remainder of this paper is organized as follows. The heterogeneous network model and the dynamic BS power consumption model are presented in Section II. The novel load balancing metric and the energy efficiency are derived in Section III. In Section IV, the optimization problems of the general and the special cases of partial connectivity are formulated, and the corresponding optimization algorithms are proposed. Simulation results and discussions are obtained in Section V with the conclusions drawn in Section VI.

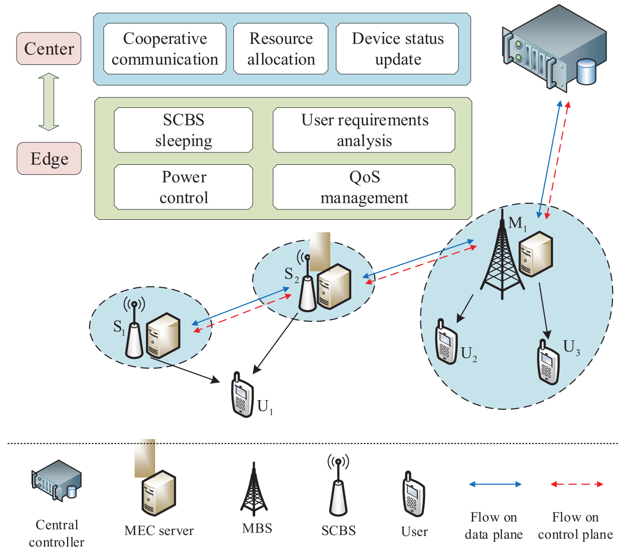

FIGURE 1. The heterogeneous network with MEC servers and a central controller.

II. SYSTEM MODEL

In this section, we apply SDN and cooperative communication to the framework of 5G network and propose a heterogeneous network model integrating MEC servers and a central controller. SDN divides the network into a control plane and a data plane, and the central controller make it better to manage the whole network, resulting in higher flexibility of the network. It can be seen from Fig. 1 that there are bidirectional transmission of message flows on the control plane and the data plane between the central controller, MEC servers and the BSs. The control plane and the data plane are separated from each other, but the control plane and the data plane can communicate through the OpenFlow protocol.

Each MEC server is physically connected to a BS while all MEC servers are directly connected to the central controller or indirectly connected to the central controller via other MEC servers. An MEC server is equivalent to a BS's local controller and has certain computing and control functions. When the service requested by the user is relatively simple, the amount of data is small, and the real-time requirement is high, just the MEC server of the BS can satisfy the user's demand, and there is not large amount of data needed to be transmitted to the central controller, thus alleviating the load of the data center. The central controller can grasp the users' status information and the dynamic information such as traffic load, transmit power, and operating mode of BSs in real time. Under normal circumstances, the entire network is controlled and managed so that the performance of the system such as connectivity probability, load balancing and energy efficiency can reach a relative optimal state. In the special case of allowing partial connectivity, the central controller may send instructions to MEC servers to adjust the operating mode or transmit power of BSs based on the status information of users and BSs to further improving the energy efficiency.

The heterogeneous cellular network is composed of an SCBS tier and an MBS tier, which are independent of each other. In the intra-tier cooperation model, the SCBS tier provides services for users through cooperative communication, and the user chooses to associate with an SCBS cooperative group or a single MBS based on the maximum received signal strength (RSS). If the user choose an SCBS cooperative group, the SCBSs not only transmit data to the user, but also transmit the user's status information to the central controller through the local MEC servers, and then the central controller sends back the feedback information, which allows the SCBSs in the same group to share the information of the common user, thus implementing cooperative communication. In the cross-tier cooperation model, the serving BS of a user is a group composed of an MBS and an SCBS, the two BSs also need to share the information of the common user to implement cooperative communication. We assume that the Orthogonal Frequency Division Multiple Access (OFDMA) is used, where the intra-cell interference is ignored, and the users are interfered by other BSs, including intra-tier interference and cross-tier interference.

In the heterogeneous network, $i \in \{m, s\}$ corresponds to the MBS tier or the SCBS tier respectively. The BSs in tier i have the transmit power p_i, and follow the homogeneous Poisson point process (PPP) $\Phi_i \in \mathbb{R}^2$ with density λ_i. It means that the density and transmit power of the BSs in two tiers are different, but the transmit power of the BSs in one tier is the same. Assuming that a typical user is at the origin, the jth BS in the tier i is $x_{i,j}$, and the distance between the BS and the typical user is $r_{i,j}$. Users, MBSs and SCBSs are assumed to be equipped with single antenna. We consider that the channel fading in both tiers is Rayleigh, and the power fading coefficient is $h_{i,j} \sim \exp(1)$. α is the path loss exponent, which is the same in both tiers. The event that the typical user accessing the MBS/SCBS tier in the intra-tier cooperation model is E_m/E_s.

In our intra-tier cooperation model, the user chooses to access an SCBS cooperative group or a single MBS based on the maximum received signal strength (RSS). The received power p_r of the user from a MBS can be expressed as $p_r = p_t h r^{-\alpha}$, where p_t is the transmit power of the BS. h is the power fading coefficient, which satisfies $h \sim \exp(1)$. α is the distance between the user and the BS. r is the path loss exponent. Since the transmit power of the BS is the same in one tier, the received power is only negatively correlated with the distance. It is obvious that the power received by the user from the nearest MBS is the strongest received power in the MBS tier. Similarly, in the SCBS tier, the strongest power received by the user comes from an SCBS cooperative group consisting of several SCBSs closest to the user.

A. CROSS-TIER COOPERATION MODEL

In the cross-tier cooperation model, a user selects the nearest MBS and the nearest SCBS as its serving BSs, and the MBS and the SCBS provide services for the same user through cooperation. It is known from [46] that the statistical characteristics of users at any location are consistent with the statistical characteristics of typical users at fixed locations. Without loss of generality, we choose the user at the origin as the typical user for analysis.

The probability density functions (PDFs) of the distance from the nearest MBS and the closest SCBS to the typical user are respectively

$$f_{r_m}(r_1) = 2\pi\lambda_m r_1 e^{-\pi\lambda_m r_1^2}, \tag{1}$$

$$f_{r_s}(r_2) = 2\pi\lambda_s r_2 e^{-\pi\lambda_s r_2^2}, \tag{2}$$

where r_1, r_2 denote the distances between the nearest MBS and the closest SCBS to the typical user respectively. (1) and (2) can be obtained by the null probability of the PPP [47].

The SINR at the typical user is [16]

$$\mathrm{SINR} = \frac{\sum_{x_{i,j}\in\mathcal{C}} p_i h_{i,j} r_{i,j}^{-\alpha}}{\sum_{x_{i,j}\in\mathcal{C}^c} p_i h_{i,j} r_{i,j}^{-\alpha} + \sigma^2}, \tag{3}$$

where $\mathcal{C}$ represents the set of serving BSs, which may be a group consisting of an MBS and an SCBS in the cross-tier cooperation model or an SCBS cooperative group/a single MBS in the intra-tier cooperation model in this paper. $\mathcal{C}^c$ denotes the set of all the interfering BSs in two tiers except the serving BSs. The numerator is the useful signal received by the typical user from the serving BSs. The first term in the denominator is the interference signal received from all other BSs except the serving BSs, including intra-tier interference and cross-tier interference, and the second term is the additive white Gaussian noise with variance σ^2. Cooperation transforms part of the interference in the denominator into the useful signal in the numerator, which increases the SINR and the coverage performance.

Theorem 1: In the cross-tier cooperation case, the connectivity probability is

$$\mathbb{P}_{\mathrm{t}} = \int_{r_1>0}\int_{r_2>0} \exp\left(\frac{-\sigma^2\Gamma}{\varphi}\right)\mathcal{L}_I\left(\frac{\Gamma}{\varphi}\right) \times f_{r_m}(r_1) f_{r_s}(r_2)\, dr_1\, dr_2, \tag{4}$$

where $\varphi = p_m r_1^{-\alpha} + p_s r_2^{-\alpha}$. σ^2 *is the variance of additive white Gaussian noise.* Γ *is the SINR threshold.* $f_{r_m}(r_1)$ *and* $f_{r_s}(r_2)$ *are given in (1) and (2) respectively.* $\mathcal{L}_I(s)$ *is the Laplace transform of the interference* I, *given by*

$$\mathcal{L}_I(s) = \prod_{i\in\{m,s\}} \exp\left(-2\pi\lambda_i (sp_i)^{\frac{2}{\alpha}} \int_{(sp_i)^{-\frac{1}{\alpha}} d_i}^{\infty} \frac{\gamma}{1+\gamma^\alpha} d\gamma\right), \tag{5}$$

where d_i *denotes the distance between the nearest interfering BS and the user in tier i, i.e.,* $d_m = r_1$ *for the MBS tier and* $d_s = r_2$ *for the SCBS tier.*

Proof: The proof is in Appendix A. ■

B. INTRA-TIER COOPERATION MODEL

In the intra-tier cooperation model, the accessing strategy for the user is that the user always selects the nearest MBS or an SCBS cooperative group that provides higher RSS as its serving BS/BSs. If the serving BS of a user is an SCBS cooperative group, the group is composed of k SCBSs that are the closest to the typical user, which is $\mathcal{B} \subset \Phi_s$. In this way, the user's Quality of Service (QoS) can be improved while the load of the two-tier BSs can be more balanced.

Lemma 1: In the intra-tier cooperation case, the probability of accessing the SCBS tier is

$$A_s = \int_0^\infty \int_{r_{s,1}}^{r_{s,3}} \cdots \int_{r_{s,k-1}}^{\infty} \times e^{-\lambda_m \pi (\eta(r))^{\frac{2}{\alpha}}} f_\Pi(r) dr_{s,1} dr_{s,2} \cdots dr_{s,k}, \quad (6)$$

where $\eta(r) = p_m/(p_s \sum_{j=1}^{k} r_{s,j}^{-\alpha})$. r_m *and* $r_{s,j}$ *denote the distances from the nearest MBS and the j-th nearest SCBS to the typical user.* $r = [r_{s,1}, r_{s,2}, \cdots, r_{s,k-1}, r_{s,k}]$ *is the set of distances between kth closest SCBSs and the typical user. The joint PDF of r is*

$$f_\Pi(r) = (2\pi\lambda_s)^k e^{-\lambda_s \pi r_{s,k}^2} \prod_{j=1}^{k} r_{s,j}. \quad (7)$$

The probability for the typical user accessing the MBS tier is $A_m = 1 - A_s$.

Proof: The proof is in Appendix B. ■

Lemma 2: In the intra-tier cooperation model, when the typical user connects to a single MBS, the PDF of the distance between the MBS and the user is

$$f_{R_m}(r) = \frac{1}{A_m} f_{r_m}(r) g(r), \quad (8)$$

where $f_{r_m}(r) = 2\pi\lambda_m r e^{-\pi\lambda_m r^2}$ *and* $g(r) = \mathrm{P}(p_m r_m^{-\alpha} > \sum_{j=1}^{k} p_s r_{s,j}^{-\alpha})$.

Proof: The PDF of the distance between the nearest MBS and the typical user can be obtained by the null probability of the PPP [47]. When the user connects to an MBS, $f_{R_m}(r)$ is a PDF given E_m. Then, we have

$$\mathrm{P}(R_m > r) = \mathrm{P}(r_m > r | E_m) \quad (9)$$

$$= \frac{\mathrm{P}(r_m > r, E_m)}{\mathrm{P}(E_m)} \quad (10)$$

$$= \frac{1}{A_m} \int_r^\infty \mathrm{P}\Big(p_m r_m^{-\alpha} > \sum_{j=1}^{k} p_s r_{s,j}^{-\alpha}\Big) f_{r_m}(r) dr, \quad (11)$$

where R_m is the distance from the serving MBS to the user when the user accesses the MBS tier. We can obtain equation (8) by calculating $f_{R_m}(r) = \frac{d\mathrm{P}(r_m > r | E_m)}{dr}$. ■

Considering $k = 2, \alpha = 4$ in the later simulations, the result can be transformed into the following equation by means of integral transformation and simplification

$$g(r) = \int_0^{\frac{\pi}{4}} \frac{\sqrt{p_m/p_s} r^{-2} + \pi\lambda_s \sin^{-1} x}{(\cos x r^{-1})^2 \sqrt{p_m/p_s}} e^{-\frac{\pi\lambda_s r^2}{\sqrt{p_m/p_s}\sin x}} dx, \quad (12)$$

Lemma 3: In the intra-tier cooperation model, when the typical user connects to an SCBS cooperation group, the PDF of the distance between the SCBS and the user is

$$f_{R_s}(r) = \frac{1}{A_s} e^{-\pi\lambda_m \eta^{2/\alpha}} f_\Pi(r). \quad (13)$$

The proof of equation (13) is similar to equation (8).

Theorem 2: In the intra-tier cooperation model, the connectivity probabilities of the typical user connecting to a single MBS and an SCBS cooperative group are respectively

$$\mathbb{P}_{\mathrm{mc}} = \int_0^\infty e^{-p_m^{-1} r^\alpha \sigma^2 \Gamma} \mathcal{L}_I\left(p_m^{-1} r^\alpha \Gamma\right) f_{R_m}(r) dr, \quad (14)$$

$$\mathbb{P}_{\mathrm{sc}} = \int_{\substack{0 < r_{s,1} < r_{s,2} \\ \cdots < r_{s,k} < \infty}} \exp\left(\frac{-\sigma^2\Gamma}{\beta}\right) \mathcal{L}_I\left(\frac{\Gamma}{\beta}\right) f_{R_s}(r) dr, \quad (15)$$

where $\beta = \sum_{j=1}^{k} p_s r_{s,j}^{-\alpha}$. Γ *is the SINR threshold.* $f_{R_m}(r)$ *and* $f_{R_s}(r)$ *are given in* (8) *and* (13). $\mathcal{L}_I(s)$ *is given by* (5). *From the proof of* (6), (8) *and* (13), *we can obtain that for* $\mathbb{P}_{\mathrm{mc}}$, *the condition is* $d_m = r$, $d_s \approx (p_s/p_m)^{1/\alpha} r$, *and for* $\mathbb{P}_{\mathrm{sc}}$, *the condition is* $d_m = \eta^{1/\alpha}$, $d_s = r_{s,k}$. *The total connectivity probability in the intra-tier cooperation case is* $\mathbb{P}_{\mathrm{c}} = A_m \mathbb{P}_{\mathrm{mc}} + A_s \mathbb{P}_{\mathrm{sc}}$.

Proof: The proof is in Appendix C. ■

C. THE BS POWER CONSUMPTION MODEL

Recent investigations on the energy consumption of cellular networks which consist of BSs, mobile terminals and the core network show that the energy consumption at the BSs accounts for more than 60% of the total energy required for the operation [48], [49]. Therefore, we mainly focus on the power consumption of BSs. The recognized linear BS power model proposed by the EARTH project [50] is often used by researchers to study the energy efficiency of wireless networks. We reserves the concept proposed by the EARTH project that the total power of a base station is a linear combination of static power and transmit power, i.e., the total power is composed of static power and load-related RF power.

In our work, the SCBS is assumed to have two operating modes: working and sleeping. In the working mode, all components of a SCBS are active, and the SCBS can provide services for users normally. But when in the sleeping mode, only some control components are active, and the SCBS cannot serve users. The power consumption model of a single SCBS is

$$p_{\mathrm{st}} = \begin{cases} p_{\mathrm{so}} + \Delta_{\mathrm{sp}}(p_s + p_h) N_1, & \text{if } p_s \neq 0 \text{ and } N_1 \leq N_s^{\max} \\ p_{\mathrm{sleep}}, & \text{if } p_s = 0, \end{cases} \quad (16)$$

where p_{st} is the total power. p_{so} denotes the static power. Δ_{sp} is the reciprocal of the radio frequency power amplifier efficiency, namely, the slope of the power related to the load. p_h is the backhaul power, which is used to transmit users' status information to the central controller. The feedback information from the central controller ensures the exchange of data between the SCBSs in the cooperative group. p_{sleep} represents the power of an SCBS in the sleeping mode.

N_1 indicates the number of users actually served by an SCBS simultaneously. $N_s^{\max}$ denotes the maximum number of users who can be served by a single SCBS.

The MBS is assumed to have only one operating mode which is the working mode. Its total power consumption is still composed of static power and load-related RF power. The power consumption model of a single MBS is

$$p_{\mathrm{mt}} = p_{\mathrm{mo}} + \Delta_{\mathrm{mp}} p_m N_2, \tag{17}$$

where $p_{\mathrm{mt}}, p_{\mathrm{mo}}, \Delta_{\mathrm{mp}}$ denote the total power, the static power and the reciprocal of the radio frequency power amplifier efficiency respectively. N_2 is the number of users served by an MBS.

III. LOAD BALANCING METRIC AND ENERGY EFFICIENCY

In this section, we propose a novel load balancing metric by virtue of the access probability of the intra-tier cooperation model in the heterogeneous network. In addition, based on the proposed BS power consumption model, the expression of the energy efficiency is obtained.

A. LOAD BALANCING METRIC

In a heterogeneous network, it is worthwhile to study whether the load in the two tiers is balanced. It is assumed that all users either access the MBS tier or the SCBS tier, and no base station is overloaded. Let λ_u be the density of users, the average numbers of users for each BS in the SCBS tier and the MBS tier are $N_s = \frac{kA_s\lambda_u}{\lambda_s}$ and $N_m = \frac{A_m\lambda_u}{\lambda_m}$. The capacity utilization ratio of the BSs in each tier, i.e., the ratio of the number of users actually served to the maximum number of users, is $N_i^r = \frac{N_i}{N_i^{\max}}$ $i \in \{s, m\}$, where $N_i^{\max}$ is the maximum number of users served by a single BS in tier $i \in \{s, m\}$. Thus, we define the load balancing metric as

$$S_N = \sum_{i\in\{s,m\}} \left(N_i^r - \frac{N_s^r + N_m^r}{2}\right)^2, \tag{18}$$

where S_N reflects the disparity of the capacity utilization ratios of BSs in two tiers. Therefore, (18) can be used to determine whether the heterogeneous network is load-balanced. The smaller S_N is, the closer the capacity utilization ratios of the BSs in two tiers are, resulting in more balanced load. When $S_N = 0$, the capacity utilization ratios of the BSs in two tiers are exactly the same, where the load balancing of the heterogeneous network is optimal.

On account of the differences of the densities of the BSs in two tiers and the ability of two types of BSs to serve users, we have not directly used the simple two-tier access probability ratio to measure the load balancing, which is inaccurate, but taken S_N as the load balancing metric, which takes more factors into consideration and is more persuasive.

B. ENERGY EFFICIENCY

Only when the instantaneous SINR of the typical user is greater than the given SINR threshold, the connectivity condition could be met. By taking advantage of the access probability and connectivity probability obtained in the previous sections, we can derive the total throughput as

$$C_t = C_s + C_m = k\mathbb{P}_{\mathrm{sc}} A_s \lambda_u R + \mathbb{P}_{\mathrm{mc}} A_m \lambda_u R, \tag{19}$$

where C_s, C_m are the throughput of each tier per square meter per second when the user is served by the MBS tier and the SCBS tier respectively. $R = B\log_2(1 + \Gamma)$ is the maximum achievable rate, and B is the channel bandwidth.

Based on the proposed BS power consumption model, we can obtain the total energy consumptions of the MBS tier and the SCBS tier per square meter per second as

$$P_{\mathrm{mt}} = p_{\mathrm{mo}}\lambda_m + \Delta_{\mathrm{mp}} p_m A_m \lambda_u, \tag{20}$$
$$P_{\mathrm{st}} = p_{\mathrm{so}}\lambda_s + k\Delta_{\mathrm{sp}}(p_s + p_h) A_s \lambda_u. \tag{21}$$

Energy efficiency is defined as the ratio of the total throughput to the energy consumption during a period of time T, namely, the amount of data transmitted per unit of energy consumed, which is measured in bps/W or bit/Joule. The expression of energy efficiency is

$$E = \frac{C_s + C_m}{P_{\mathrm{st}} + P_{\mathrm{mt}}}. \tag{22}$$

As can be seen from the definition of energy efficiency, energy efficiency is determined by both throughput and energy consumption, which only involves the energy cost in the total cost of the system. We will conduct further research on the total cost of the system in the follow-up work, and it is necessary to consider other costs such as deployment cost at that time.

IV. SYSTEM OPTIMIZATION

In this section, the utility model is established to quantify the impact of different factors on the network performance. Considering multiple performance metrics, we propose a method for the overall performance optimization. In the case of partial connectivity, the energy efficiency can be improved by the proposed discrete stochastic optimization algorithm.

A. UTILITY FUNCTION

Utility is a concept in microeconomics that indicates how satisfied consumers are in purchasing goods. Utility theory is the theory of how consumers distribute their income among various goods and services to maximize satisfaction. Utility theory can also be used in wireless communication [51]. The utility function reflects the relationship between attribute values and utility values. We use the common Sigmoid function as follows to study the relationship between the network's parameters and the performance utility.

$$\mathrm{U}(x) = \frac{1}{1 + e^{\xi(\mu - x)}} \quad (\xi > 0, \mu > 0), \tag{23}$$

where ξ is the maximum slope of the tangent line of the curve, and μ is the midpoint of the variation interval of attribute values.

B. UTILITY OPTIMIZATION

By applying the utility theory, the main influencing factors correspond to the consumption of consumers, and the performance corresponds to the consumer satisfaction. Using the utility function (23), the load balancing, the connectivity probability and the energy efficiency are

$$\mathrm{U}_N = \frac{1}{1+e^{\xi_N(\mu_N+S_N)}}, \tag{24}$$

$$\mathrm{U}_{\mathbb{P}_c} = \frac{1}{1+e^{\xi_P(\mu_P-\mathbb{P}_c)}}, \tag{25}$$

$$\mathrm{U}_E = \frac{1}{1+e^{\xi_E(\mu_E-E)}}, \tag{26}$$

where U_N, $\mathrm{U}_{\mathbb{P}_c}$ and U_E are utility functions of load balancing, connectivity probability and energy efficiency respectively. Therefore, we define the total utility of the heterogeneous network as

$$\mathrm{U}_t = w_1\mathrm{U}_N + w_2\mathrm{U}_{\mathbb{P}_c} + w_3\mathrm{U}_E,\ (w_1+w_2+w_3=1), \tag{27}$$

where w_1, w_2 and w_3 are the weights of the three utilities in the total utility respectively.

The capacity utilization ratio of the BSs, the connectivity probability, and the energy efficiency of the network are all dependent on the density ratio λ_s/λ_m. As a consequence, U_N, $\mathrm{U}_{\mathbb{P}_c}$, U_E can all be expressed as a function of λ_s/λ_m, so the total utility can be transformed into

$$\mathrm{U}_t(\frac{\lambda_s}{\lambda_m}) = w_1\mathrm{U}_N(\frac{\lambda_s}{\lambda_m}) + w_2\mathrm{U}_{\mathbb{P}_c}(\frac{\lambda_s}{\lambda_m}) + w_3\mathrm{U}_E(\frac{\lambda_s}{\lambda_m}). \tag{28}$$

Intuitively, as λ_s/λ_m increases, U_N, $\mathrm{U}_{\mathbb{P}_c}$ and U_E will show the trend of decreasing, increasing, increasing first and decreasing later respectively, which can be verified in the following simulations. Therefore, an optimal density ratio $(\lambda_s/\lambda_m)^*$ can be found to make the total utility reach a maximum value, which means that the network can simultaneously achieve a more balanced load, a higher connectivity probability as well as a higher energy efficiency. The weights of various types of utility can be adjusted to meet different demands, and it is significant to explore the optimal density ratio. Thus, we can formulate the following utility optimization problem

$$obj.\ \left(\frac{\lambda_s}{\lambda_m}\right)^* = \arg\max_{\lambda_s/\lambda_m\in\Theta} \mathrm{U}_t\left(\frac{\lambda_s}{\lambda_m}\right) \tag{29}$$

$$s.t.\ \ C1: \mathrm{U}_t\left(\frac{\lambda_s}{\lambda_m}\right) = w_1\mathrm{U}_N + w_2\mathrm{U}_{\mathbb{P}_c} + w_3\mathrm{U}_E \tag{30}$$

$$C2: \Theta = \left\{\frac{\lambda_s}{\lambda_m}\left|\frac{\lambda_s}{\lambda_m}\in[1,100], \frac{\lambda_s}{\lambda_m}\in\mathbb{N}\right.\right\} \tag{31}$$

$$C3: w_1+w_2+w_3=1. \tag{32}$$

The density ratio λ_s/λ_m is a continuous value and difficult to implement for deployment. Therefore, we assume that λ_s/λ_m is an integer on the interval $[1, 100]$. The optimal density ratio and the maximum total utility can be obtained by using a regular exhaustive search algorithm.

C. PARTIAL CONNECTIVITY

For long-term monitoring applications such as habitat animal behavior monitoring and climate monitoring, it is not necessary to ensure full connectivity, but to save energy with high energy efficiency. For these applications, allowing partial connectivity will not degrade the usability of the application and the experience of users. Instead, it can certainly reduce the total energy consumption of the network. Therefore, it is significant to study the relationship between the partial connectivity and the energy efficiency of the heterogeneous network.

Partial connectivity means that the connectivity probability between the BS and the user can be reduced by changing certain parameters of the network, that is to say, some BSs are invisible to users and cannot provide normal services for users, leaving only another part of BSs to become serving BSs. There are two feasible ways to make the network be partially connected: (1) changing the transmit power of BSs (2) letting some BSs sleep.

In the case with partial connectivity, all MBSs are in the working mode, but some SCBSs are in the sleeping mode. In order to reduce the total energy consumption, some SCBSs should be switched from the working mode to the sleeping mode. If some nodes are randomly removed from the homogeneous PPP, the remaining nodes still follow the homogeneous PPP. Assuming that the actual working rate of the SCBS is δ. The density of the SCBSs that can serve users is $\lambda_s' = \delta\lambda_s$. It should be noted that, the total power consumption of the SCBS tier no longer conforms to (21) but is in accordance with the following equation

$$P_{st}' = p_{so}\delta\lambda_s + k\Delta_{sp}(p_s+p_h)A_s'\lambda_u + (1-\delta)\lambda_s p_{\text{sleep}}. \tag{33}$$

Under the condition of allowing partial connectivity, the optimal energy efficiency of the network can be expressed as the following discrete stochastic optimization problem

$$obj.1\ \ p_s^* = \arg\max_{p_s\in\Omega_p} E\left(L\left(p_s\right)\right) \tag{34}$$

$$s.t.\ \ C1: \mathrm{P}_1 \le \mathbb{P}_c \le \mathrm{P}_2. \tag{35}$$

The optimization object 1 refers to the optimal transmit power p_s^* when the energy efficiency is maximized with the fixed actual working rate, where $L\left(p_s\right)$ is the corresponding load state information. $C1$ is the specific condition of partial connectivity. In each time slot, the central controller can only obtain the load status estimated information $\hat{L}\left(p_s\right)$. It is assumed that $E(n, \hat{L}(p_s))$ is an unbiased estimate of $E\left(L\left(p_s\right)\right)$. Therefore, the optimization object 1 becomes

$$p_s^* = \arg\max_{p_s\in\Omega_p} E\left(L\left(p_s\right)\right) = \arg\max_{p_s\in\Omega_p} \mathbb{E}\left[E\left(n, \hat{L}\left(p_s\right)\right)\right]. \tag{36}$$

For optimization problem (36), different methods can be used to solve it. A solution is that for each possible transmit power $p_s^l \in \Omega_p$, we first determine whether it satisfies the

Algorithm 1 : Exhaustive Search Algorithm Based On Partial Connectivity

1. Initialization
the central controller gives all the possible SCBS transmit power to compose the set Ω_p
for $p_s^l \in \Omega_p, l = 1, 2, \ldots, \kappa$ **do**
2. Judgment and computing
feedback the load state information $L(p_s^l)$ to the central controller and obtain $\mathbb{P}_c\left(L(p_s^l)\right)$
if $\mathrm{P}_1 \le \mathbb{P}_c\left(L(p_s^l)\right) \le \mathrm{P}_2$
the central controller computes $\hat{E}_N\left(L\left(p_s^l\right)\right)$ and insert it into the set Ξ
end if
end for
3. Sort
sort all $\hat{E}_N\left(L\left(p_s^l\right)\right) \in \Xi, l = 1, 2, \ldots, \vartheta$ in ascending order, obtain $\hat{E}_N\left(L\left(p_s^1\right)\right) \le \hat{E}_N\left(L\left(p_s^2\right)\right) \le \ldots \le \hat{E}_N\left(L\left(p_s^\vartheta\right)\right)$
4. Output
return $p_s^* = p_s^\vartheta, E_{\max}=E\left(L\left(p_s^*\right)\right), E_{\min}=E\left(L\left(p_s^1\right)\right)$

condition $C1$, and then calculate the following equation

$$\hat{E}_N\left(L\left(p_s\right)\right) = \frac{1}{N}\sum_{n=1}^{N} E\left(n, \hat{L}\left(p_s\right)\right). \tag{37}$$

Finally we select the optimal transmit power $p_s^* = \arg\max_{p_s\in\Omega_p} \hat{E}_N(L(p_s))$ from all possible transmit power. According to the law of large numbers, when $N \to \infty$, we can obtain $\hat{E}_N(L(p_s)) \to \mathbb{E}[E(n, \hat{L}(p_s))]$. Therefore, we first propose an exhaustive search algorithm based on partial connectivity, which is shown in algorithm 1.

Obviously, algorithm 1 is too computationally intensive. In order to reduce the computation, we propose a discrete stochastic optimization algorithm based on partial connectivity according to [52] and [53], which utilizes the state transition probability matrix of Markov chain. The state transition probability vector is defined to record the probability that all possible transmit power is selected at each iteration time, which can be expressed as

$$p=\left[\mathrm{p}(1, p_s^{(1)}), \mathrm{p}(2, p_s^{(2)}), \ldots, \mathrm{p}(t, p_s^{(t)}) \ldots\right]^{\mathrm{T}}, \tag{38}$$

where $\mathrm{p}(t, p_s^{(t)}) = (number\_of\_chosen\, p_s^{(t)})/M$, $\mathrm{p}(t, p_s^{(t)}) \in [0, 1]$ and $\sum_{t=1}^{M} \mathrm{p}(t, p_s^{(t)})=1$. M is the total number of iterations. The process of updating the state transition probability is

$$\mathrm{p}(t+1, p_s^{(t+1)}) = \mathrm{p}(t, p_s^{(t)})+\varpi(t+1)(\mathbf{D}(t+1) - \mathrm{p}(t, p_s^{(t)})), \tag{39}$$

where $\varpi(t) = 1/t$ is the iteration step, which will decrease with time. $\mathbf{D}(t+1)$ is a vector that the t+1th element is 1 and all the other elements are 0, whose dimension is the same as $\mathbf{p}$. The specific implementation of the algorithm is shown in algorithm 2. Since the state transition probability is a cumulative quantity, it first increases as the number of iterations increases and then tends to be stable, algorithm 2 can converge to the optimal value quickly. But algorithm 1 cannot obtain the optimal value until the algorithm is completely finished. Therefore, the convergence speed of algorithm 2 is faster than that of algorithm 1, which can be confirmed by the subsequent simulations.

Algorithm 2 : Discrete Stochastic Optimization Algorithm Based On Partial Connectivity

1. Initialization
(a) the central controller gives all the possible SCBS transmit power to form the set Ω_p
(b) initialize time $t = 0$
(c) select an initial SCBS transmit power $p_s^{(1)} \in \Omega_p$ and set $\mathrm{p}(t, p_s^{(1)}) = 1$
(d) for all $p_s \neq p_s^{(1)}$, set $\mathrm{p}(t, p_s) = 0$
for $t = 1, 2, 3, \ldots$ **do**
2. Iteration
(a) given $p_s^{(t)}$ and choose another $\tilde{p}_s^{(t)} \in \Omega_p \backslash p_s^{(t)}$ randomly at iteration time t
(b) feedback the load state information $L(p_s^{(t)}), L(\tilde{p}_s^{(t)})$ to the central controller
(c) the central controller obtains $\mathbb{P}_c(L(p_s^{(t)}))$, $\mathbb{P}_c(L(\tilde{p}_s^{(t)}))$, $E(L(p_s^{(t)}))$ and $E(L(\tilde{p}_s^{(t)}))$
3. Judgment and acceptance
if $\mathrm{P}_1 \le \mathbb{P}_c(L(p_s^{(t)})) \le \mathrm{P}_2$ and $\mathrm{P}_1 \le \mathbb{P}_c(L(\tilde{p}_s^{(t)})) \le \mathrm{P}_2$
if $E(L(p_s^{(t)})) < E(L(\tilde{p}_s^{(t)}))$
set $p_s^{(t+1)} = \tilde{p}_s^{(t)}$
else
set $p_s^{(t+1)} = p_s^{(t)}$
end if
end if
4. Update state transition probabilities
compute $\mathrm{p}(t+1, p_s^{(t+1)}) = \mathrm{p}(t, p_s^{(t)}) + \varpi(t+1)(D(t+1) - \mathrm{p}(t, p_s^{(t)}))$, and the iteration step is $\varpi(t) = \frac{1}{t}$
5. Determine the maximum
if $\mathrm{p}(t+1, p_s^{(t+1)}) > \mathrm{p}(t+1, \hat{p}_s^{(t)})$
set $\hat{p}_s^{(t+1)} = p_s^{(t+1)}$
else
set $\hat{p}_s^{(t+1)} = \hat{p}_s^{(t)}$
end if
end for
6. Output
return $p_s^* = \hat{p}_s^{(t+1)}, E_{\max}=E(L(p_s^*))$

Although algorithm 1 and algorithm 2 are proposed for optimization object 1, which requires a fixed actual working rate of the SCBSs, the principles of both algorithms can also be applied to optimization object 2 as follows

$$obj.2\ \ \delta^* = \arg\max_{\delta\in\Omega_\delta} E\left(L\left(\delta\right)\right) \tag{40}$$

$$s.t.\ \ C'1 : \mathrm{P}_3 \le \mathbb{P}_c \le \mathrm{P}_4. \tag{41}$$

TABLE 1. Simulation parameters.

Notation	Parameter	Value
λ_m	Density of MBSs	$\frac{1}{500^2\pi}m^{-2}$
α	Path loss exponent	4
σ^2	Variance of noise	0
k	Number of SCBSs in an cooperation group	2
p_m	MBS transmit power	30W
p_h	SCBS backhaul power for cooperation	0.25W
p_{mo}	MBS static power	130W
p_{so}	SCBS static power	20W
p_{sleep}	SCBS sleeping power	8W
Δ_{mp}	MBS power amplifier efficiency reciprocal	4.7
Δ_{sp}	SCBS power amplifier efficiency reciprocal	4.0
$N_m^{\max}$	Maximum number of users for each MBS	500
$N_s^{\max}$	Maximum number of users for each SCBS	100
B	Bandwidth	10MHz

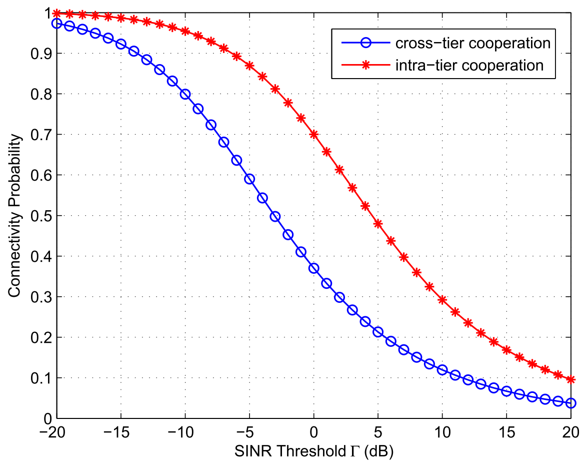

FIGURE 2. Comparison of connectivity probability for the cross-tier and intra-tier cooperation cases ($\lambda_s = \frac{40}{500\pi^2}m^{-2}$, $p_s = 1$W).

The optimization object 2 refers to the optimal actual working rate δ^* when the energy efficiency of the network is maximized with the fixed transmit power of the SCBSs. $C'1$ is the specific condition of partial connectivity.

V. NUMERICAL RESULTS AND DISCUSSIONS

In this section, we evaluate the network performance through numerical results. Based on the utility theory, the corresponding BS density ratio to optimize the network performance is obtained. Moreover, the impact of BS working rate, transmit power, and connectivity on the energy efficiency is also explored under the condition of partial connectivity. Part of parameters for the simulations are presented in the Table I.

A. CONNECTIVITY PROBABILITY

Fig. 2 gives a comparison of the connectivity probabilities in the cross-tier and intra-tier cooperation cases. The connectivity probabilities in both cases tend to decrease as the SINR threshold Γ increases. When fixing Γ, we observe that the connectivity probability in the intra-tier cooperation case is always larger than that in the cross-tier cooperation case. When $\Gamma = 0$dB, the difference between them is obvious.

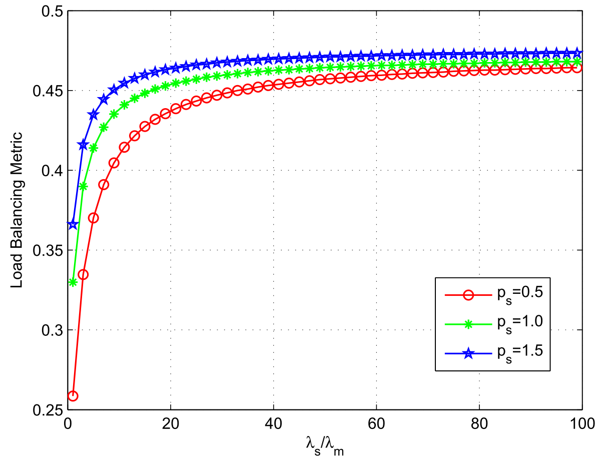

FIGURE 3. The load balancing metric for different λ_s/λ_m and p_s ($\Gamma = 5$dB).

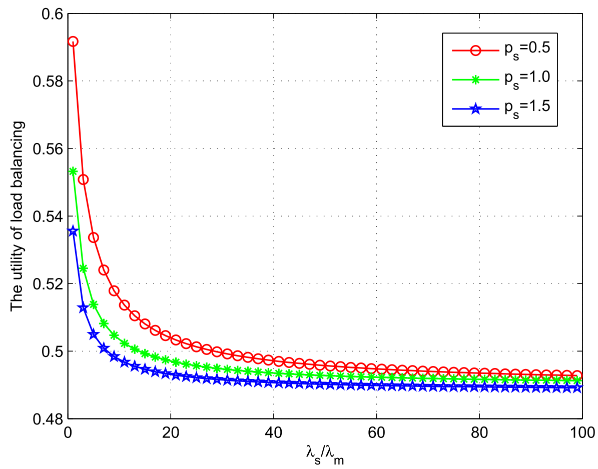

FIGURE 4. The utility of load balancing for different λ_s/λ_m and p_s ($\Gamma = 5$dB).

In the following discussions, we focus on other performance metrics and the utility optimization problems.

B. NETWORK UTILITY OPTIMIZATION

Fig. 3 and Fig. 4 show the load balancing metric and the load balancing utility trend with BS density ratio respectively. As λ_s/λ_m or p_s increases, the load balancing metric tends to increase, and the speed of ascending is getting slower. At the moment of λ_s/λ_m=1, the capacity utilization of the SCBSs is already larger than that of the MBSs in our scenario. When the SCBSs are deployed more densely or the transmit power becomes greater, the signal received by the user from the SCBS cooperative group is enhanced. As a result, a large number of users will no longer access the MBS tier, but will access the SCBS tier, causing that N_s^r increases while N_m^r decreases. Therefore, S_N gets larger, which means that the load balancing metric becomes bigger. Combined with equation (26), we can easily understand the trend shown in Fig. 4. We can draw the conclusion that if the SCBSs are

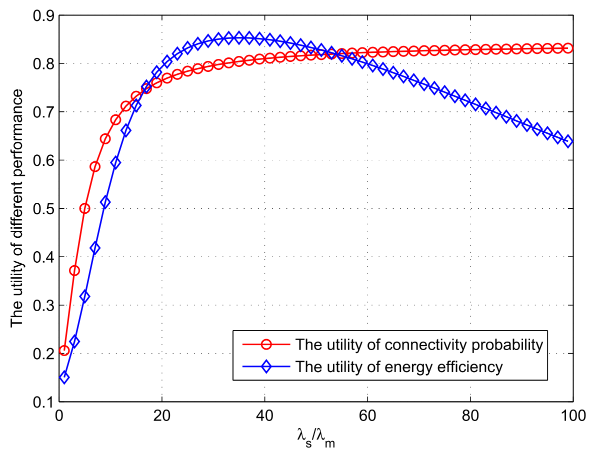

FIGURE 5. **The utility of connectivity probability and energy efficiency with different λ_s/λ_m (p_s = 1W, Γ = 5dB).**

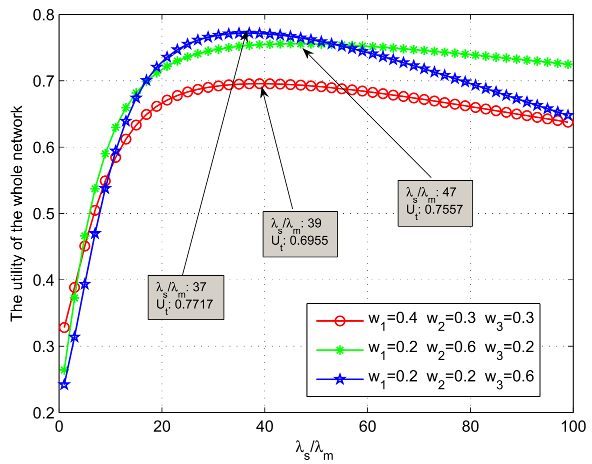

FIGURE 6. **The utility of the whole network for different λ_s/λ_m and weights (p_s = 1W, Γ = 5dB).**

deployed too densely, it will lead to a serious imbalance in the load. Thus, it is crucial to set λ_s/λ_m reasonably.

The effect of the BS density ratio on the connectivity probability and energy efficiency is shown in Fig. 5. Through simulations, we know that under any SINR threshold, the connectivity probability of the SCBS tier is always bigger than that of the MBS tier, i.e., $\mathbb{P}_{\mathrm{sc}} > \mathbb{P}_{\mathrm{mc}}$ (the simulation diagram is not given here). When λ_s/λ_m increases, more users will access the SCBS tier, and the load offloading speed gets slower. Finally, it will reach $A_s \rightarrow 1, A_m \rightarrow 0$. From $\mathbb{P}_{\mathrm{c}} = A_m\mathbb{P}_{\mathrm{mc}} + A_s\mathbb{P}_{\mathrm{sc}}$, we can learn that the total connectivity probability will ascend, and the growth rate will gradually descend. With the growth of λ_s/λ_m, the energy efficiency increases first and then decreases. Since energy efficiency is determined by both throughput and energy consumption. In the early period, the increase in throughput is faster than the increase in power consumption, but it is reversed later.

Fig. 6 depicts the total utility as functions of the BS density ratio for different weights. Although the weights are different, all of the total utilities show a trend of rising first and then decreasing. There is always a maximum value, but the

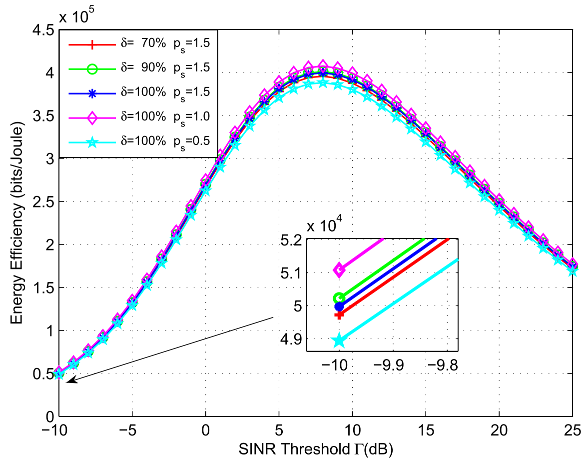

FIGURE 7. **Comparison of the energy efficiency for different δ and p_s ($\lambda_s = \frac{50}{500^2\pi}\mathrm{m}^{-2}$, p_{sleep} = 8W).**

corresponding optimal λ_s/λ_m is different. The optimal density ratio and the maximum utility value can be obtained by a regular exhaustive search algorithm. By comprehensively considering the three utilities, it is not difficult to draw a conclusion that the optimal density ratio (39 or 37) when the weight of U_N or U_E is the largest is smaller than the optimal density ratio (47) when the weight of $\mathrm{U}_{\mathbb{P}_c}$ is the biggest. Therefore, we can adjust the weights of U_N, $\mathrm{U}_{\mathbb{P}_c}$ and U_E to meet different actual needs.

C. PARTIAL CONNECTIVITY

The five different conditions are (1) $\delta = 70\%, p_s = 1.5$w (2) $\delta = 90\%, p_s = 1.5$w (3) $\delta = 100\%, p_s = 1.5$w (4) $\delta = 100\%, p_s = 1$w (5) $\delta = 100\%, p_s = 0.5$w respectively, where the first three cases and the last three cases are two sets of comparison items. As can be seen from Fig. 7, when any SINR threshold is fixed, the energy efficiency satisfies (2)>(3)>(1) and (4)>(3)>(5) while the connectivity probability satisfies (1)<(2)<(3) and (5)<(4)<(3) (the simulation diagram is omitted). It indicates that appropriately reducing the working rate or transmit power of SCBSs which results in partial connectivity can indeed be used to improve the energy efficiency. However, if the rate and transmit power of SCBSs are blindly reduced to pursue low energy consumption, it will result in a decrease in energy efficiency, which is inexpedient. Therefore, the central controller and the MEC servers should make suitable changes to the SCBSs in accordance with the user requirement to improve the energy efficiency.

When the SINR threshold is fixed to -10 dB, a number of $(\mathbb{P}_c, E)$ pairs characterizing the relationship between the connectivity probability and energy efficiency can be obtained by fine-tuning the transmit power of SCBSs. In Fig. 8, it can be seen from the blue curve of δ=1 when the connectivity probability is reduced from 99.2% to 93.5%, the energy efficiency ascends first and descends later, but it is always no less than the energy efficiency when the connectivity probability is 99.2%. The green and red curves of δ=0.9 and

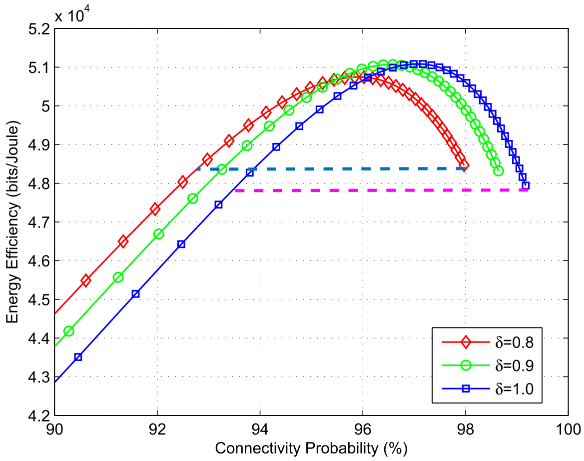

FIGURE 8. **Relationship between connectivity probability and energy efficiency for different** ***m*** **($\lambda_s = \frac{50}{500^2\pi} m^{-2}$, $P_{sleep} = 8W$, $\Gamma = -10dB$).**

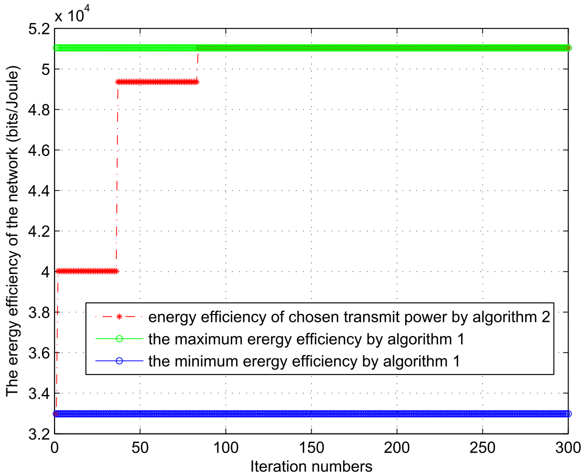

FIGURE 9. **Run of algorithm 2: Energy efficiency of the network for the chosen transmit power versus iteration numbers with the fixed actual working rate of SCBSs. ($\delta = 90\%$, $\lambda_s = \frac{50}{500^2\pi} m^{-2}$, $P_{sleep} = 8W$, $\Gamma = -10dB$, P_1=0.95, P_2=0.99).**

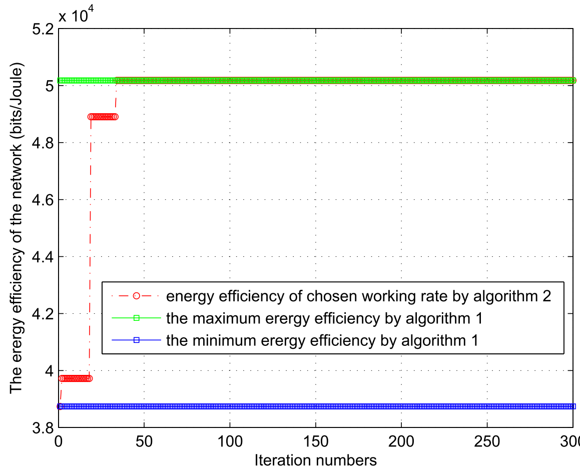

FIGURE 10. **Run of algorithm 2: Energy efficiency of the network for the chosen actual working rate versus iteration numbers with the fixed transmit power of SCBSs. ($p_s = 1.5W$, $\lambda_s = \frac{50}{500^2\pi} m^{-2}$, $P_{sleep} = 8W$, $\Gamma = -10dB$, P_3=0.95, P_4=0.99).**

δ=0.8 have the same tendency as the blue curve. And there is always a maximum value. Therefore, when the users' service is allowed to be partially connected, the central controller will send instructions to the MEC servers to make some adjustments to δ and p_s, thereby improving the energy efficiency.

In Fig.9, we consider the performance of algorithm 2 to select the optimal transmit power of the SCBSs that maximizes the energy efficiency of the heterogeneous network, where the actual working rate of the SCBSs is fixed at $\delta = 90\%$. In each iteration of algorithm 2, the transmit power is randomly generated. It can be seen from the red curve that algorithm 2 adaptively converge to the optimal transmit power, and the maximum and minimum energy efficiency obtained by both algorithms are correspondingly approximately equal, indicating that algorithm 2 is effective. The optimal transmit power and energy efficiency obtained by the two algorithms are almost the same, which are $p_s^* = 1.1$W, $E(L(p_s^*)) = 5.1 * 10^4$ bits/Joule. Through simulations, we observe that the time spent by algorithm 2 is significantly less than that of algorithm 1, which is consistent with the theoretical analysis in the 8th paragraph of Section IV, part C. Since the operation of the algorithm 2 requires a short amount of time, the previous optimal transmit power of the SCBSs will not change until the central controller calculates the next one, that is, the transmit power between the two decisions remains unchanged, which is in line with the actual fact. We can draw a conclusion that algorithm 2 is more suitable for our network scenario.

In Fig.10, we consider the performance of algorithm 2 to choose the optimal actual working rate of the SCBSs maximizing the energy efficiency of the heterogenous network with the fixed transmit power of the SCBSs, which is $p_s = 1.5$W. The optimal actual working rate and the maximum energy efficiency obtained by algorithm 1 and algorithm 2 are correspondingly approximately the same, which are $\delta^* = 87\%$, $E(L(\delta^*)) = 5.0{*}10^4$ bits/Joule.

VI. CONCLUSIONS

In this paper, a heterogeneous network model integrating a central controller and MEC servers is proposed. The central controller is used to implement intra-tier cooperation between SCBSs and dynamic management of the whole network while MEC servers are used for the power control and operating mode management of base stations. A novel load balancing metric and a BS power consumption model which takes the number of users into consideration are presented to analyze the load balancing and energy efficiency of the network. According to the utility theory, we propose a method for the overall optimization of the network, where multiple performance metrics are considered. In addition, in the special case of partial connectivity, the central controller can send instructions to adjust transmit power or operating mode of the SCBSs to obtaining the maximum energy efficiency through the discrete stochastic optimization algorithm. Simulation results indicate that the proposed method can optimize the communication system according to actual requirements of the users.

APPENDIX A
PROOF OF THEOREM 1

The connectivity probability refers to the probability that the SINR actually received by the typical user is greater than the given SINR threshold Γ. Therefore, in the cross-tier cooperation model, the connectivity probability is

$$\begin{aligned}\mathbb{P}_{\mathrm{t}} &= \Pr\left(\frac{p_m h_{m,1} r_1^{-\alpha} + p_s h_{s,1} r_2^{-\alpha}}{I+\sigma^2} > \Gamma\right)\\ &\overset{(a)}{=} \Pr\left(h > \frac{(I+\sigma^2)\Gamma}{p_m r_1^{-\alpha} + p_s r_2^{-\alpha}}\right)\\ &\overset{(b)}{=} \mathbb{E}_{r_1,r_2}\left[\exp\left(\frac{-\sigma^2\Gamma}{\varphi}\right)\cdot \mathcal{L}_I\left(\frac{\Gamma}{\varphi}\right)\right]\\ &= \int_{r_1>0}\int_{r_2>0}\exp\left(\frac{-\sigma^2\Gamma}{\varphi}\right)\mathcal{L}_I\left(\frac{\Gamma}{\varphi}\right)\\ &\quad\times f_{r_m}(r_1) f_{r_s}(r_2)\, dr_1 dr_2, \end{aligned} \tag{42}$$

where $\varphi = p_m r_1^{-\alpha} + p_s r_2^{-\alpha}$. (a) is due to the hypothesis $h_{i,j} \sim \exp(1)$, while (b) takes advantage of the Laplace transform of the interference I, $\mathcal{L}_I(s)=e^{-sI}$.

The Laplace transform of I can be derived as

$$\begin{aligned}\mathcal{L}_I(s) &= \mathbb{E}_I[e^{-sI}]\\ &\overset{(c)}{=} \mathbb{E}\left[e^{-s\sum_{\Phi_{I_i}}\sum_{i\in\{m,s\}} p_i h_{i,j} r_{i,j}^{-\alpha}}\right]\\ &\overset{(d)}{=} \prod_{i\in\{m,s\}} \mathbb{E}\left[\prod_{\Phi_{I_i}} \frac{1}{1+sp_i r_{i,j}^{-\alpha}}\right]\\ &\overset{(e)}{=} \prod_{i\in\{m,s\}} \exp\left(-\lambda_i \int_{\mathbb{R}^2}\left(1-\frac{1}{1+sp_i r^{-\alpha}}\right)dr\right)\\ &\overset{(f)}{=} \prod_{i\in\{m,s\}} \exp\left(-2\pi\lambda_i (sp_i)^{\frac{2}{\alpha}} \int_{(sp_i)^{-1/\alpha}d_i}^{\infty} \frac{\gamma}{1+\gamma^\alpha} d\gamma\right), \end{aligned} \tag{43}$$

where Φ_{I_i} is the set of all interfering BSs in tier i. (c) is because the interference I consists of all BSs except $x_{m,1}$ and $x_{s,1}$ in two tiers. (d) makes use of the expression of the moment generation function for the exponential random variable $h_{i,j}$. (e) follows from the probability generation functional (PGFL) that for any function $f(x)$ conforming to $x \in \Phi$, we have $\mathrm{E}\left[\prod_{x\in\Phi} f(x)\right] = \exp\left(-\lambda \int_{\mathbb{R}^d}(1-f(x))dx\right)$. (f) uses the variable substitution $\gamma^\alpha = (sp_i)^{-1} r^\alpha$. The calculation is an integral from d_i to ∞ in tier i, where d_i is the distance between the nearest interfering BS and the user in tier i.

APPENDIX B
PROOF OF LEMMA 1

When the RSS at the typical user from an SCBS cooperative group is greater than that from a single MBS, the user will access the SCBS tier, so the probability is

$$\begin{aligned}A_s &= \mathrm{P}\left(\sum_{j=1}^{k} p_s r_{s,j}^{-\alpha} > p_m r_m^{-\alpha}\right)\\ &= \mathbb{E}\left[\mathrm{P}\left(r_m > \left(p_m \Big/ \left(p_s \sum_{j=1}^{k} r_{s,j}^{-\alpha}\right)\right)^{\frac{1}{\alpha}}\right)\right]\\ &= \int_{\substack{0<r_{s,1}<r_{s,2}\\ \cdots<r_{s,k}<\infty}} \mathrm{P}\big(r_m > (\eta(r))^{1/\alpha}\big) f_\Pi(r)\, dr. \end{aligned} \tag{44}$$

It is a well-known theorem that the null probability of PPP with density λ in the region $\mathcal{A}$ is $\mathrm{P}(\mathrm{N(BS)} = 0) = \exp(-\lambda S(\mathcal{A}))$, where N(BS), $S(\mathcal{A})$ denote the number of the BS and the area of the region respectively. $r_m > (\eta(r))^{1/\alpha}$ means that there is no MBS in the circle with radius $(\eta(r))^{1/\alpha}$ in the MBS tier. Thus, we can obtain the following equation

$$\mathrm{P}\left(r_m > \left(p_m \Big/ \left(p_s \sum_{j=1}^{k} r_{s,j}^{-\alpha}\right)\right)^{\frac{1}{\alpha}}\right) = e^{-\lambda_m \pi (\eta(r))^{\frac{2}{\alpha}}}. \tag{45}$$

The joint PDF of the distances between the two nearest BSs and the user has been given in [54]. Similarly, the PDF of $r_{s,j}$ in the intra-tier cooperation model can be obtained by using the null probability theorem and the Bayes formula as

$$f_\Pi(r) = (2\pi\lambda_s)^k e^{-\lambda_s \pi r_{s,k}^2} \prod_{j=1}^{k} r_{s,j}. \tag{46}$$

APPENDIX C
PROOF OF THEOREM 2

Only when the actual SINR received by the typical user is greater than the given threshold Γ, the serving BS can provide services for the user. Therefore, in the intra-tier cooperation model, the derivation process of equation (14) is as follow:

$$\begin{aligned}\mathbb{P}_{\mathrm{mc}} &= \Pr\left(\frac{p_m h_{m,1} r_m^{-\alpha}}{I+\sigma^2} > \Gamma\right)\\ &= \Pr\left(h_{m,1} > p_m^{-1} r_m^\alpha \Gamma (I+\sigma^2)\right)\\ &\overset{(g)}{=} \mathbb{E}_{r_m}\left[\exp\left(-p_m^{-1} r_m^\alpha \Gamma\sigma^2\right)\mathcal{L}_I(p_m^{-1} r_m^\alpha \Gamma)\right]\\ &= \int_0^\infty \left(\exp(-p_m^{-1} r_m^\alpha \Gamma \sigma^2)\mathcal{L}_I(p_m^{-1} r_m^\alpha\Gamma)\right) f_{R_m}(r)\, dr, \end{aligned} \tag{47}$$

where (g) takes advantage of the laplace transform of I, $\mathcal{L}_I(s)=e^{-sI}$. $\mathcal{L}_I(s)$ can be found in (5).

The proof of equation (15) is similar to equation (14).

Due to the complexity of the proposed intra-tier cooperation model, the analytical expressions we obtained can no longer be further simplified. Although the expressions contain several integrals, it is worth noticing that we can use the integral tools provided by Matlab to solve them easily. Therefore, we can clearly evaluate the impact of important parameters on network performance through the simulation results.

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TAO HAN (M'13) received the Ph.D. degree in information and communication engineering from the Huazhong University of Science and Technology (HUST), Wuhan, China, in 2001. From 2010 to 2011, he was a Visiting Scholar with the University of Florida, Gainesville, FL, USA, as a Courtesy Associate Professor. He is currently an Associate Professor with the School of Electronic Information and Communications, HUST. His research interests include wireless communications, multimedia communications, and computer networks. He is currently serving as an Area Editor for the *EAI Endorsed Transactions on Cognitive Communications*.

SHIMIN LI received the bachelor's degree in communication engineering from Central South University (SCU), Changsha, China, in 2017. She is currently pursuing the master's degree with the Huazhong University of Science and Technology (HUST), Wuhan, China. Her research interests include cooperative communications, heterogeneous networks, and SDN.

YI ZHONG (S'12–M'16) received the B.S. and Ph.D. degrees in electronic engineering from the University of Science and Technology of China (USTC), in 2010 and 2015, respectively. Since 2012, he has been a Visiting Student with the Prof. Martin Haenggi's Group, University of Notre Dame. Since 2013, he has been an Research Intern with Qualcomm Incorporated, Corporate Research and Development, Beijing. From 2015 to 2016, he was a Postdoctoral Research Fellow with the Wireless Networks and Decision Systems (WNDS) Group, Singapore University of Technology and Design (SUTD), led by Prof. T. Q.S. Quek. He is currently an Assistant Professor with the School of Electronic Information and Communications, Huazhong University of Science and Technology, Wuhan, China. His current research interests include heterogeneous and femtocell-overlaid cellular networks, wireless ad hoc networks, stochastic geometry, and point process theory.

ZHIQUAN BAI (M'07) received the M.Eng. degree in communication and information system from Shandong University, Jinan, China, in 2003, and the Ph.D. degree (Hons.) in communication engineering from INHA University, in 2007, under the Grant of Korean Government IT Scholarship, Incheon, South Korea. From 2007 to 2008, he held a Postdoctoral position with INHA University, Incheon. From 2015 to 2016, he was a Visiting Professor with The University of British Columbia, Kelowna, Canada. Since 2007, he has been an Associate Professor with the School of Information Science and Engineering, Shandong University, China. His current research interests include cooperative and MIMO systems, visible light communication, cognitive radio networks, resource allocation and optimization, and 5G wireless communications.

KYUNG-SUP KWAK (M'81) received the M.S. and Ph.D. degrees from the University of California at San Diego, in 1981 and 1988, respectively. From 1988 to 1989, he was with Hughes Network Systems, San Diego, CA, USA. From 1989 to 1990, he was with the IBM Network Analysis Center, Research Triangle Park, NC, USA. Since 1990, he has been with the School of Information and Communication Engineering, Inha University, South Korea, as a Professor, where he was the Dean of the Graduate School of Information Technology and Telecommunications, from 2001 to 2002. He has been the Director of the UWB Wireless Communications Research Center, South Korea, since 2003. In 2006, he served as the President of the Korean Institute of Communication Sciences and the Korea Institute of Intelligent Transport Systems, in 2009. His research interests include wireless communications, ultrawideband systems, sensor networks, wireless body area networks, and nanocommunications. He received a number of awards, including the Engineering College Achievement Award from Inha University, the LG Paper Award, the Motorola Paper Award, the Haedong Prize of Research, and various government awards from the Ministry of ICT, the President, and the Prime Minister of Korea, for his excellent research performances.