

# User Association and Wireless Backhaul Bandwidth Allocation for 5G Heterogeneous Networks in the Millimeter-Wave Band

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**Abstract:** The user association and wireless backhaul bandwidth allocation for a two-tier heterogeneous network (HetNet) in the millimeter wave (mmWave) band is proposed in this article. The two-tier HetNet is built up with a macro base station (MBS) and several small cell SBSs, where the MBS is assumed to be equipped with large-scale antenna arrays but the SBSs only have single-antenna capability and they rely on the wireless link to the MBS for backhaul. The sum of logarithmic user rate, which is established according to the result of multi-user Multiple Input Multiple Output (MIMO) downlink employing Zero-Force Beamforming (ZFBF), is chosen as the network utility for the objective function. And a distributed optimization algorithm based on primal and dual decomposition is used to jointly optimize the user association variable  $x_{j,i}$  and the wireless backhaul bandwidth factor  $\beta$ . Simulation results reveal that the distributed optimization algorithm jointly optimizing two variables outperforms the conventional SINR-based user association strategies.

**Keywords:** millimeter wave; massive MIMO; ZFBF; user association; bandwidth allocation

## I. INTRODUCTION

With exponentially increasing demand for data traffic in the past decade and the foreseen future, the radio spectrum suitable for long range high rate wireless communications is becoming more and more scarce. Thus, an increasing number of novel wireless communication technologies are proposed. A cluster-nuclei based model for wireless channel is proposed in the literature [1], considering the big data research progress. In literature [2], 6–100 GHz research progress and challenges from a channel perspective for the fifth generation (5G) and future wireless communication are analyzed. Millimeter wave (mmWave) communications technology described in the literature [3][4][5], due to the vastly available bandwidth, has been attracting increasing attention from both academia and industry in the past few years [6][7]. By combining mmWave communications with heterogeneous network (HetNet) architecture, flexible wireless access of massive mobile terminals (MTs) can be supported, especially when wireless backhaul and large-scale antenna arrays technologies come into play [8][9][10]. However, with the

This paper proposes a scheme for solving the user association and wireless backhaul bandwidth allocation problem in a two-tier HetNet at the mmWave band.

conventional signal-to-interference-plus-noise ratio (SINR) based user association schemes, the macro base station (MBS) tends to attract much more users than the small cell base station (SBS) due to the different transmit power and antenna configuration in the two-tier HetNet, which results in the communication congestion [11]. In this case, an efficient source allocation and user association method aiming at load balancing should be concerned.

There are a plenty of literature studying cell association and resource allocation. The related works on user association and resource allocation can be divided into two groups:

- Schemes for realizing the fairness of the entire network and promoting user experiences: a biasing approach attempting to offload traffic of BS is proposed in the literature [12]. The user association is done using cell range extension (CRE) and the resource allocation is divided orthogonally in the spectrum to minimize the outage probability [13]. Load balancing across networks with massive MIMO and the utility function emphasizing fairness are considered in the literature [14].
- Schemes for maximizing the system throughput: a user association method is proposed aiming at obtaining maximal throughput under the wireless backhaul constraints [10]. A heuristic dynamic cell association method is investigated to achieve the maximum sum rate of all users [15]. A network utility function of the long-term rate for each user is optimized by distributed optimization algorithms [11][16]. This kind of strategy maximizes the system throughput but fails to address the fairness issue.

All these papers do not jointly consider user association and wireless backhaul resource allocation in a multi-tier HetNet with large-scale antenna arrays at the mmWave band. It is well known, user association and resource allocation are closely related and the backhaul constraints play an important part in the overall system capacity in wireless communication. Therefore, this paper investigates a distributed

optimization algorithm to solve the optimization problem of biased user association and constrained wireless backhaul bandwidth allocation. The contributions of this paper are listed as follow:

- This paper jointly optimizes the user association sub-problem and wireless backhaul bandwidth resource sub-problem in a two-tier HetNet with large-scale antenna arrays at the mmWave band. Additionally, a biasing factor on SINR is introduced to keep the fairness of the system.
- A distributed optimization algorithm based on primal and dual decompositions is used to solve the optimization problem. The original problem is decomposed into a wireless backhaul bandwidth allocation sub-problem and a user association sub-problem. And the user association sub-problem is solved in its Lagrange dual problem.
- The simulation results verify that the system throughput was improved by increasing the number of users and the large-scale antenna array size. And by comparing with the conventional user association method, the distributed optimization algorithm has an obvious advantage in improving the system throughput.

The rest of the paper is arranged as follows. A system model is introduced in Section II. In Section III, the objective function is established and solved by the distributed optimization algorithm. Numerical simulations and analysis are discussed in Section IV. Finally, a conclusion is made in Section V.

## II. SYSTEM MODEL

### 2.1 The deployment of BSs and users in the HetNet with massive MIMO

As shown in figure 1, in the two-tier HetNet, the macro BS (MBS) equipped with  $N_m$  antennas is located in the center of the area, while the small BSs (SBSs) and mobile terminals (MTs) are both only equipped with a single antenna in the coverage range of MBS. The

set of MTs is defined as  $\mathcal{U}$  and the set of SBSs is denoted by  $\mathcal{B}$ .  $\mathcal{B}_0 = \mathcal{B} \cup \{0\}$  is the set of all BSs, where 0 is the indicator of MBS. The configuration parameters are given in table 1.

As for the beamforming gain, it is different between the access link of MBS and the backhaul link. Since the number of SBS is much small than the antenna array size of MBS, each backhaul link between the SBS and MBS is served by one beamforming group. And assume that the channel state information (CSI) is completely known by BS, the beamforming gain of the backhaul link is derived as  $\left(\frac{N_m - N_{sc}}{N_{sc}}\right)$  according to ZFBF [17][18].

But for the access link of MBS, the number of users  $N_u$  is much more than  $N_m$ , so we use the user grouping method to calculate the beamforming gain of the access link. All the users associated with MBS can be divided into  $\frac{\sum_{i \in \mathcal{U}} x_{0,i}}{N_g}$  groups, where  $\sum_{i \in \mathcal{U}} x_{0,i}$  is the number of users served by MBS, and  $N_g$  is the number of beamforming group, which means that different group user use different access bandwidth and users in the same group are served by the same bandwidth but different beam. Thus, the beamforming gain of the access link of MBS is  $\left(\frac{N_m - N_g}{N_g}\right)$  [17][18].

## 2.2 Downlink SINR bias and interference arrangement

In the conventional scheme, users associated with the BS with the maximal SINR in downlink, which makes the MBS over-loaded. Therefore, an SINR bias approach is investigated.

**Definition 1.** Assuming the factor  $A_j$  for the  $j^{th}$  BS, the biased SINR received by the  $i^{th}$  user from the  $j^{th}$  BS is defined as follow:

$$SINR'_{j,i} = A_j \cdot SINR_{j,i}. \quad (1)$$

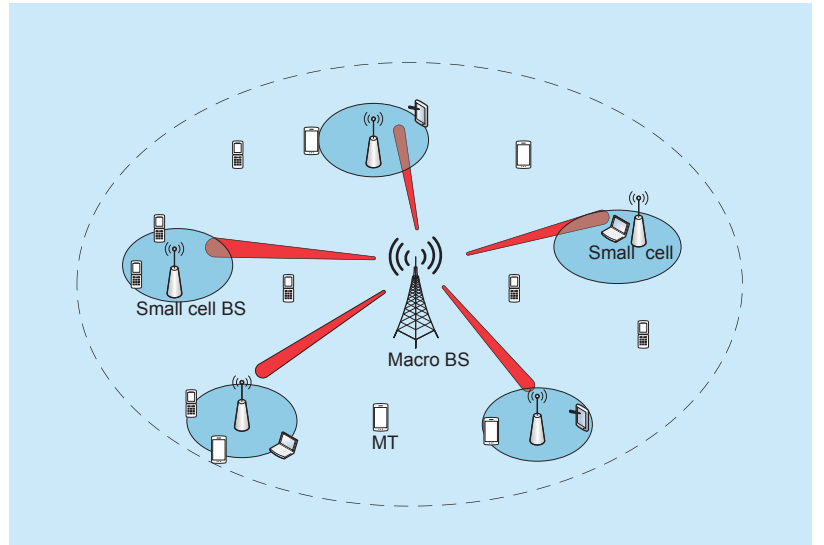
The SINR bias approach offloads users from the heavy-load MBS to the light-load SBSs, which guarantees the fairness of the

HetNet and especially improves the rate of cell-edge users.

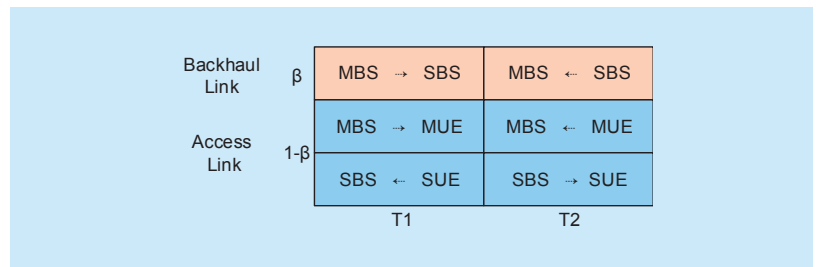
In addition, the transmission of the MBS has a serious interference to the close by SBSs, if they have the same time slot configuration

**Table I.** Configuration in the two-tier HetNet system model.

Parameter	Value
Antenna array size at MBS ( $N_m$ )	100 to 200
Antenna element type	Omni-directional antenna
Antenna gain of MBS	0 dBi
Antenna gain of SBS	8 dBi
MBS Tx power	40 dBm
SBS Tx power	33 dBm
The height of MBS	25 m
The height of SBS	10 m
The average height of MT	1.5 m
The number of SBS ( $N_{sc}$ )	5
The number of MT ( $N_u$ )	100 to 800



**Fig. 1.** A two-tier HetNet with multiple small cell BSs and a single macro BS equipped with large-scale antenna arrays.



**Fig. 2.** Interference elimination mechanism.

during an association period. Hence, a flexible Time Division Duplex (TDD) called reverse TDD (RTDD) is investigated [19]. In RTDD, the MBS is in the downlink (DL) mode while

all the SBSs are in the uplink (UL) mode and vice versa. Based on the RTDD, the SBS simultaneously receives signals from its users and the MBS in the UL mode, which causes the interference. Therefore, the soft frequency reuse (SFR) is introduced to solve the problem. The frequency bandwidth is divided into two parts expressed by  $\beta$  and  $(1-\beta)$ , where  $\beta$  is for the backhaul link and  $(1-\beta)$  is for the access link if we consider the whole wireless bandwidth resource as a unit. The RTDD and SFR work well on the interference avoidance in the two-tiers HetNet as shown in figure 2.

### 2.3 The simulation scenarios

There are an open rural scenario and a Manhattan urban scenario used to verify the correctness of the channel model and the closed-form expression of sum logarithmic user rate.

The open rural scenario is a square area with a range of  $500 \times 500 \text{ m}^2$ , where an MBS is deployed on the center shown as the red point and 5 SBSs are randomly deployed shown as the blue points in figure 3. In addition, 800 users are randomly deployed on the square area.

The Manhattan urban scenario is an area with a range of  $500 \times 500 \text{ m}^2$  where BSs are linearly arranged along the street in the middle of two rows of tall buildings in figure 4. And there is an MBS shown as the red point and 5 SBSs shown as the blue points. Additionally, 400 users are randomly deployed on the street forming the line-of-sight (LOS) transmission and another 400 users are randomly deployed on the north open spaces of buildings forming the non-line-of-sight (NLOS) transmission.

### 2.4 The wireless channel model

The 3rd Generation Partnership Project (3GPP) has proposed the wireless channel models for LOS scenario and NLOS scenario in 3GPP TR 38.901 standard [20]. But the wireless channel models in 3GPP are deterministic empirical path loss models, which cannot totally express the CSI in a specific environment especially in NLOS scenario, as for

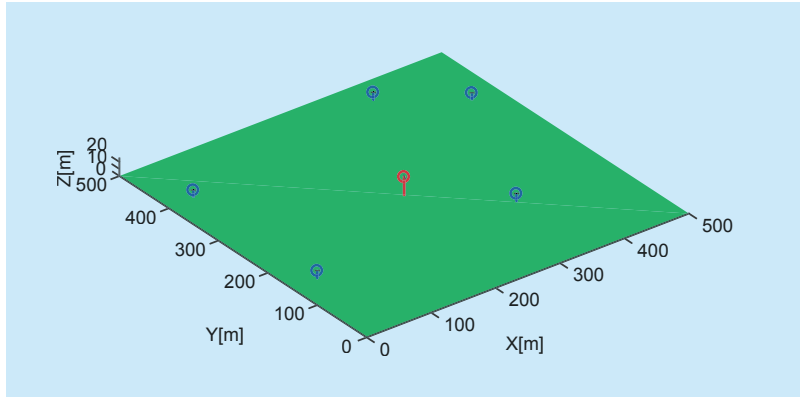


Fig. 3. Open rural scenario.

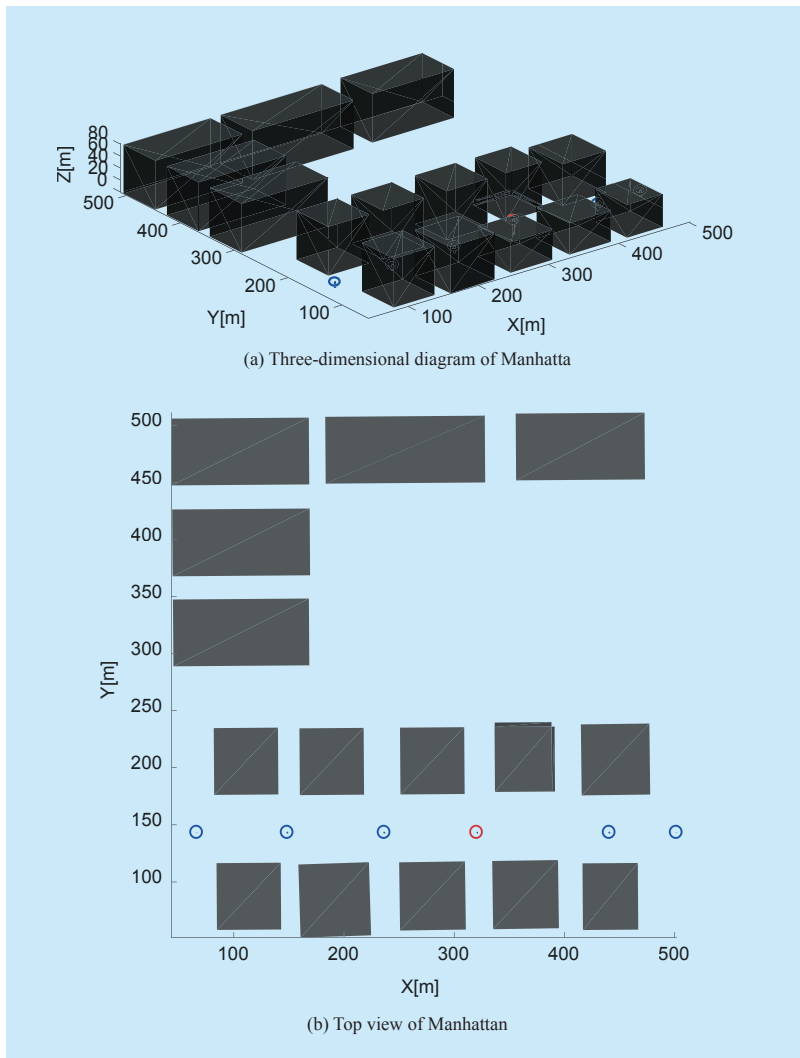


Fig. 4. Manhattan urban scenario.

the Manhattan scenario. Thus, we use the Ray Tracing (RT) method to establish the wireless channel model, which generates the corresponding wireless channel model according to the actual scenes. A comparison of 3GPP model and RT model in the path loss at 30 GHz is shown in figure 5.

It is clearly shown in figure 5, the blue curve of RT LOS path loss is very close to the red curve of 3GPP LOS path loss, which verifies the correctness of the wireless LOS channel model in RT. As for the NLOS path loss, the RT NLOS path loss is calculated by a specific scenario, so it makes no sense to compare the value of NLOS path loss calculated by the two methods. But we can distinctly see that both the curve of RT NLOS path loss and the curve of 3GPP NLOS path loss have the same tendency. Therefore, in the following simulations, the wireless channel model is generated by RT for the rural scenario and the urban scenario. And the RT simulation parameters are given in table 2.

### III. A DISTRIBUTED OPTIMIZATION ALGORITHM FOR USER ASSOCIATION AND WIRELESS BACKHAUL BANDWIDTH ALLOCATION

#### 3.1 Optimal objective function

We next give the following definitions before formulating the optimization function for the long-term sum of logarithmic user rate.

**Definition 2.** The long-term rate of the  $i^{th}$  user associated with the  $j^{th}$  BS is given by

$$R_{j,i} = \sum_{j \in B_0} y_{j,i} \times \log_2(1 + SINR'_{j,i}), \quad (2)$$

where  $y_{j,i}$  denotes the fraction of resource received by the  $i^{th}$  user from the  $j^{th}$  BS and  $\sum_i y_{j,i} = 1, \forall j \in B_0$ .

**Definition 3.** If the  $i^{th}$  user is associated with the  $j^{th}$  BS, the relationship is denoted by a binary indicator  $x_{j,i}$  as below

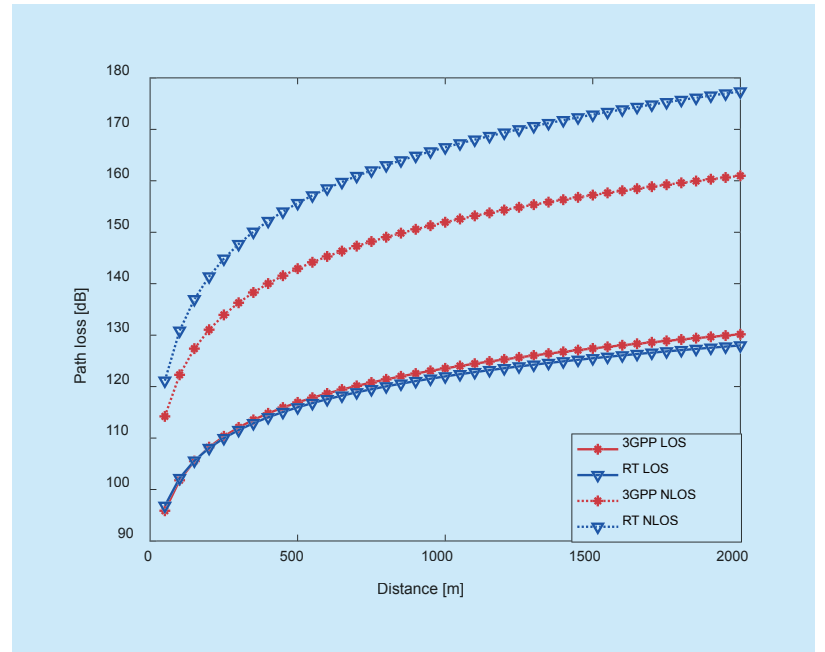
$$\sum_{j \in B_0} x_{j,i} = 1, \forall i \in \mathcal{U}, \quad (3)$$

where  $x_{j,i} \in \{0,1\}$  describes the association between the  $i^{th}$  user and the  $j^{th}$  BS.  $x_{j,i} = 1$  indicates connection and  $x_{j,i} = 0$  indicates no connection.

**Definition 4.** We define the SINR from the MBS to the  $i^{th}$  user as  $SINR'_{0,i} = \frac{A_0 P_0 \bar{H}_i}{N_0}$ , where  $A_0 = 1$  denotes no bias on macro tier and  $P_0 = 10$  is the transmit power of the MBS. In addition,  $N_0$  is the noise power and  $\bar{H}_i$  is the channel gain between the MBS and the  $i^{th}$  user. Similarly,  $SINR'_j = \frac{A_0 P_0 \bar{G}_j}{N_0}$  is the SINR

**Table II.** Simulation configuration in Ray Tracing.

Propagation Mechanism and Parameter	Propagation Model and Parameter Value
Centre frequency	30 GHz
Bandwidth	200 MHz
Noise power spectral density	-174 dBm/Hz
Material	Concrete and tempered glass
Direction mechanism	Free space
Reflection mechanism	Fresnel reflection (2 orders)
Scattering mechanism	Single lobe directive model
Transmission mechanism	Thickness $\times$ loss coefficient
Diffraction mechanism	Uniform theory of diffraction



**Fig. 5.** Comparison of 3GPP model and RT model.

from the MBS to the  $j^{th}$  SBS. The received SINR from the  $j^{th}$  SBS to the  $i^{th}$  user is denoted by  $SINR'_{j,i} = \frac{A_j P_j \bar{L}_{j,i}}{N_0 + \sum_{l \in B, l \neq j} P_l \bar{L}_{l,i}}$ , where

$A_j = 6$  is the SINR biasing factor for the  $j^{th}$  SBS and  $P_j = 2$  is the transmit power of the  $j^{th}$  SBS.

**Definition 5.** For convenience, we make some definitions of base-line rate as:

$$r_{0,i} = N_g \log_2 \left( 1 + \frac{N_m - N_g}{N_g} \cdot SINR'_{0,i} \right), \forall i \in \mathcal{U}, \quad (4)$$

$$r_{j,i} = \log_2 (1 + SINR'_{j,i}), \forall (j,i) \in B \times \mathcal{U}, \quad (5)$$

$$c_j = \log_2 \left( 1 + \frac{N_m - N_{sc}}{N_{sc}} \cdot SINR'_j \right), \forall j \in B, \quad (6)$$

where formula (4) is the access link base-line rate of MBS, formula (5) is the access link base-line rate of SBS and formula (6) is the backhaul link base-line rate. Additionally,

the  $\left( \frac{N_m - N_g}{N_g} \right)$  is the beamforming gain of

the access link and the  $\left( \frac{N_m - N_{sc}}{N_{sc}} \right)$  is beam-

forming gain of the backhaul link. And the

$N_g = \text{ceil}(\frac{N_m}{10})$  is the number of beamforming groups.

Therefore, the long-term sum of logarithmic user rate of the  $j^{th}$  BS and the throughput of the  $j^{th}$  wireless backhaul link are given by

$$R_j = \sum_{i \in \mathcal{U}} x_{j,i} \log \left( \frac{(1-\beta)r_{j,i}}{\sum_{i \in \mathcal{U}} x_{j,i}} \right), \quad (7)$$

$$C_j = \beta c_j, \quad (8)$$

where  $\frac{(1-\beta)}{\sum_{i \in \mathcal{U}} x_{j,i}}$  is the bandwidth resource di-

vided to each user associated with the  $j^{th}$  BS. Owing to the backhaul restriction, we make  $R_j \leq C_j$  to guarantee the capacity of backhaul link greater than that of the access link.

By relaxing the binary variable  $x_{j,i}$  to  $[0, 1]$ , the sum of logarithmic user rate is rewrit-

ten as

$$\text{maximize}_{\beta, X} R(\beta, X) = \sum_{j \in B_0} \sum_{i \in \mathcal{U}} x_{j,i} \log \left( \frac{(1-\beta)r_{j,i}}{\sum_{i \in \mathcal{U}} x_{j,i}} \right) \quad (9)$$

$$\text{Subject to} \quad \sum_{j \in B_0} x_{j,i} = 1, \forall i \in \mathcal{U}, \quad (10)$$

$$x_{j,i} \in \{0, 1\}, \forall (j,i) \in B_0 \times \mathcal{U}, \quad (11)$$

$$R_j \leq C_j, \forall j \in B, \quad (12)$$

$$0 \leq \beta \leq 1. \quad (13)$$

It is a function over  $\beta$  and  $X$ . The optimization problem can be worked out by finding the optimal  $X^*$  and  $\beta^*$ .

### 3.2 Primal decomposition and dual decomposition

The multi-objective optimization is solved by the hierarchical decomposition which contains the primal decomposition and the dual decomposition. The former decomposition is used to decompose the original problem with a direct resource allocation while the latter decomposition decomposes the Lagrange dual problem with a resource allocation via pricing [21]. Firstly, the original problem formula (9) is decomposed into a backhaul resource allocation sub-problem (RAP) and a user association sub-problem (UAP) by the primal decomposition. And the bandwidth resource allocation is executed at the MBS. Secondly, the dual decomposition method decomposes the UAP into the problem about  $x_{j,i}$  and the problem about  $M_j$  via the price of  $\sum_{j \in B_0} x_{j,i} = 1$  and

$M_j = \sum_{i \in \mathcal{U}} x_{j,i}$ , which can be solved separately

on local BSs side and users side.

The UAP and RAP are written as:  
UAP:

$$\text{maximize}_X \sum_{j \in B_0} R'_j(X) = \sum_{j \in B_0} \sum_{i \in \mathcal{U}} x_{j,i} \log \frac{r_{j,i}}{\sum_{i \in \mathcal{U}} x_{j,i}}, \quad (14)$$

$$\text{Subject to} \quad x_{j,i} \in \{0, 1\}, \forall (j,i) \in B_0 \times \mathcal{U}, \quad (15)$$

$$\sum_{j \in B_0} x_{j,i} = 1, \forall i \in \mathcal{U}, \quad (16)$$

$$R_j(X; \beta) \leq C_j(X; \beta), \forall j \in B. \quad (17)$$



$$\text{RAP: maximize } N_u \log(1-\beta) + \sum_{j \in B_0} R_j'(X^*), \quad (18)$$

$$\text{Subject to } 0 \leq \beta \leq 1, \quad (19)$$

$$R_j(X^*; \beta) \leq C_j(X^*; \beta), \forall j \in B. \quad (20)$$

The UAP is a concave problem subjected to the constraints of the user association and the wireless backhaul allocation [22]. The RAP is a monotonically decreasing function over a variable  $\beta$  since the  $X^* = \{x_{j,i}^*; (j,i) \in B_0 \times \mathcal{U}\}$  is obtained from the UAP. Therefore, we concern more about how to solve the UAP. By introducing an auxiliary variable  $M_j = \sum_{i \in \mathcal{U}} x_{j,i}$ ,  $\forall j \in B_0$ , the UAP is solved by the dual decomposition [21] [22]. Two Lagrange multipliers are denoted as  $\mu = [\mu_0, \mu_1, \dots, \mu_{N_{sc}}]^T$  and  $v = [0, v_1, \dots, v_{N_{sc}}]^T$  to reformulate the Lagrangian function.

$$\begin{aligned} L(X, \mu, v) &= \sum_{j \in B_0} \sum_{i \in \mathcal{U}} x_{j,i} \log(r_{j,i}) \\ &\quad - \sum_{j \in B_0} M_j \log(M_j) + \sum_{j \in B_0} \mu_j (M_j - \sum_{i \in \mathcal{U}} x_{j,i}) \\ &\quad + \sum_{j \in B_0} v_j [\beta c_j M_j - (1-\beta) \sum_{i \in \mathcal{U}} x_{j,i} r_{j,i}] \\ &= \sum_{i \in \mathcal{U}} \sum_{j \in B_0} x_{j,i} [\log(r_{j,i}) - \mu_j - v_j (1-\beta) r_{j,i}] \\ &\quad + \sum_{j \in B_0} M_j [\mu_j - \log(M_j) + v_j \beta c_j] \end{aligned} \quad (21)$$

The corresponding Lagrange dual function is defined as:

$$g(\mu, v) = \sup_x L(X, \mu, v). \quad (22)$$

And then the Lagrange dual decomposition is used to decompose the Lagrange dual function into two sub-problems.

$$g(\mu, v) = \sum_{i \in \mathcal{U}} g_i(\mu, v) + g_M(\mu, v). \quad (23)$$

The Lagrange dual problem is formulated as:

$$D: \text{minimize } \sum_{i \in \mathcal{U}} g_i(\mu, v) + g_M(\mu, v). \quad (24)$$

The dual problem is a convex problem and the optimal duality gap is zero when the strong duality holds in Karush-Kuhn-Tucker or Slater's condition [22]. That means the solution of the UAP can be obtained in its Lagrange dual problem.

The binary variable  $x_{j,i}$  is updated with a throughput maximizing mechanism.

$$x_{j,i}^{(t+1)} = \begin{cases} 1, & j = j_i^{(t)} \\ 0, & j \neq j_i^{(t)} \end{cases}, \quad \forall i \in \mathcal{U}, \quad (25)$$

where

$$j_i^{(t)} = \arg \max_{j \in B_0} [\log(r_{j,i}) - \mu_j^{(t)} - v_j^{(t)} (1-\beta) r_{j,i}],$$

$\forall i \in \mathcal{U}$ .  $M_j^{(t+1)}$  is updated by making the first order derivative zero to find the maximum of  $g_M(\mu, v)$  since  $g_M(\mu, v)$  is a concave function.  $\mu_j^{(t+1)}$  and  $v_j^{(t+1)}$  are updated with Subgradient Algorithms in an appropriate step size as  $l_\mu^{(t)}$  and  $l_v^{(t)}$ , respectively since the function is non-differentiable.

According to the constrain (12), the wireless backhaul bandwidth allocation factor  $\beta$  is updated by

$$\beta = \max \left\{ \frac{\sum_{i \in \mathcal{U}} x_{j,i}^* r_{j,i}}{\sum_{i \in \mathcal{U}} x_{j,i}^* (r_{j,i} + c_j)}, \forall j \in B \right\}, \quad (26)$$

which is taken into the UAP to find out  $X^*$  until both sub-problems converge. The convergence criterion is that the value of  $\beta$  and the Lagrange multipliers do not change anymore as shown in table 3 which means that the  $X$  is in stable. After obtaining the optimal solutions  $X^*$  and  $\beta^*$ , the sum of logarithmic user rate can be calculated according to the formula (9).

### 3.3 Simulation process

Based on the formula in Section 3.1 and Section 3.2, the simulation process is arranged as in table 3, where a and b are both threshold value to control the accuracy of inner and outer convergence respectively.

## IV. SIMULATION RESULTS AND DISCUSSION

In this section, the comparisons of simulation results in the open rural scenario and Manhattan urban scenario are analyzed. And the distributed optimization algorithm for the user association and the wireless backhaul bandwidth allocation is compared with the traditional SINR-based method and the CRE approach.

**Table III.** *Simulation process.*

**A distributed optimization algorithm for user association and wireless backhaul bandwidth allocation**

**Step1:** Generate a distribution diagram and calculate large-scale channel gain  $\bar{H}_i$ ,  $\bar{G}_j$  and  $\bar{L}_{j,i}$

**Step2:** Calculate the base-line rate  $r_{j,i}$ ,  $r_{0,i}$  and  $c_j$ ,  $\forall j \in B, i \in \mathcal{U}$

**Step3:** Execute the iterations

**While**  $\beta^{(t+1)} - \beta^{(t)} \geq a$  (the RAP does not converge at macro BS) **do**

**While**  $\mu^{(t+1)} - \mu^{(t)} \geq b$  or  $v^{(t+1)} - v^{(t)} \geq b$  (the UAP does not converge) **do**

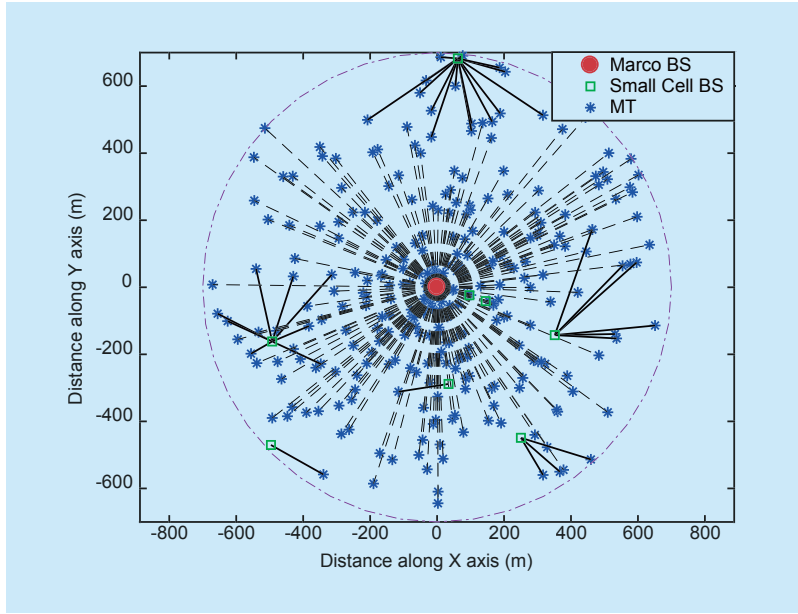
Update  $x_{j,i}^{(t+1)}$ ,  $\forall i \in \mathcal{U}, j \in B_0$  according to formula (25) until getting the inner optimal solution  $X^*$

**end**

Calculate  $\beta = \max \left\{ \frac{\sum_{i \in \mathcal{U}} x_{j,i}^* r_{j,i}}{\sum_{i \in \mathcal{U}} x_{j,i}^* (r_{j,i} + c_j)}, \forall j \in B \right\}$  until getting the outer optimal solution

$\beta^*$

**end**



**Fig. 6.** *User association of the two-tier HetNet without SINR bias.*

In addition, a biasing factor on SINR is added into the distributed optimization algorithm to offload loads of MBS into the lightly loaded SBSs.

The transmit and receive antenna gain of the SBSs is 8 dBi but 0 dBi for MTs. The transmit power at the MBS is set to be 40 dBm while the transmit power at the SBSs is set as 33 dBm.  $N_{sc}$  SBSs and  $N_u$  users are deployed in the macro cell range. The beamforming groups generated by  $N_m$  antenna elements of

MBS serve the users associated with MBS and the SBSs in the backhaul links.

By comparing figure 6 and figure 7, we can find that almost 6% users from the macro cell are transferred into the small cell by adding the SINR biasing factor  $A = 6$ , when 300 users are randomly deployed in a circle range with a radius of 600 m. It is obvious that the biasing factor on SINR works well in load balancing. In the following simulations, the SINR bias is added to the distributed optimization algorithm.

As shown in figure 8, the dotted lines are the simulation results of Manhattan urban scenario while the solid lines are the results of open rural scenario. The ‘M’ and ‘R’ in the legend respectively indicates Manhattan urban scenario and rural scenario.

We can see three key points in this figure. Firstly, the sum of logarithmic user rate is improved as the number of antennas is increased in the two scenarios with the three different methods. This is because that the beamforming at the MBS is not only used for the wireless backhaul link communication but also applied to the access link communication of MBS. Both the rate of the access link and the backhaul link are increased with the beamforming gain. Secondly, the sum of logarithmic user rate of Manhattan urban scenario is lower than that of open rural scenario due to higher path loss in the urban scene as well as the different deployment of BSs and users in these two scenarios. Thirdly, by comparing the same number of antenna array size, we can always find that the distributed optimization method is the best one, but the SINR-based method has the worst performance. This is because the distributed optimization method jointly optimizes the backhaul bandwidth resource and the user association which makes it more rational in resource allocation. The SINR-based method only considers the user association without SINR bias, so it is lowest in the sum of logarithmic rate. The CRE approach also only cares about the user association with an SINR bias, which avoids MBS overloaded, thus it is better than SINR-based method.



We can see in figure 9, the wireless backhaul bandwidth allocation factor  $\beta$  is decreased by increasing the number of antennas. This is because each wireless backhaul link is served by the one beamforming group, and the beamforming gain is increased by increasing the number of antennas, in which the capacity of each backhaul link is improved. The wireless backhaul bandwidth factor  $\beta$  for the backhaul link is decreased since the capacity of each backhaul link is improved. Meanwhile, we can find that the  $\beta$  calculated in Manhattan urban scenario is lower than that of open rural scenario owing to a different deployment of BSs. In the open rural scenario, the SBSs are far from the MBS. But the SBSs are linearly arranged along the street and close to the MBS in Manhattan urban scenario. Thus, the quality of backhaul link in Manhattan is better than that of open rural scenario, for which the Manhattan scenario needs a lower  $\beta$ .

In figure 10, the black dotted line is a reference line drawn by the first two points of ‘Optimal user association M’. By comparing with the reference line, it can be found that the sum of logarithmic user rate is improved but the slope is gradually decreased when we increase the number of MTs, which means the system will be saturated when the number of MTs reaches a large enough scale. And the sum of logarithmic user rate based on the distributed optimization algorithm is greater than that of the SINR-based method as well as that of the CRE approach.

Additionally, the gap is getting wider between the distributed optimization algorithm and the SINR-based method as well as between the distributed optimization algorithm and the CRE method when the number of the MTs is increasing in figure 11. It is because that the SINR-based method and the CRE method only concern user association according to the maximal received SINR rule. While the distributed optimization algorithm jointly optimizes the user association and the wireless backhaul bandwidth allocation which improves the resource utilization. This effect

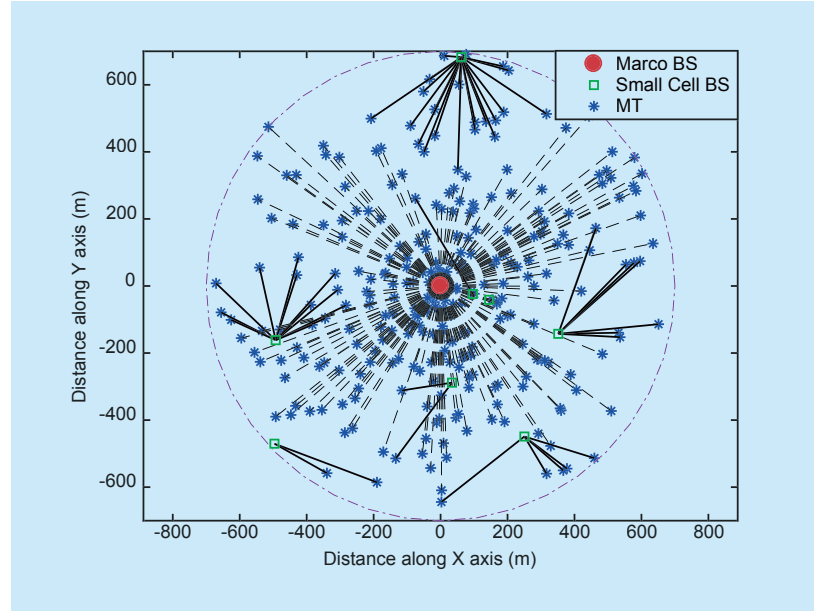


Fig. 7. User association of the two-tier HetNet with SINR bias.

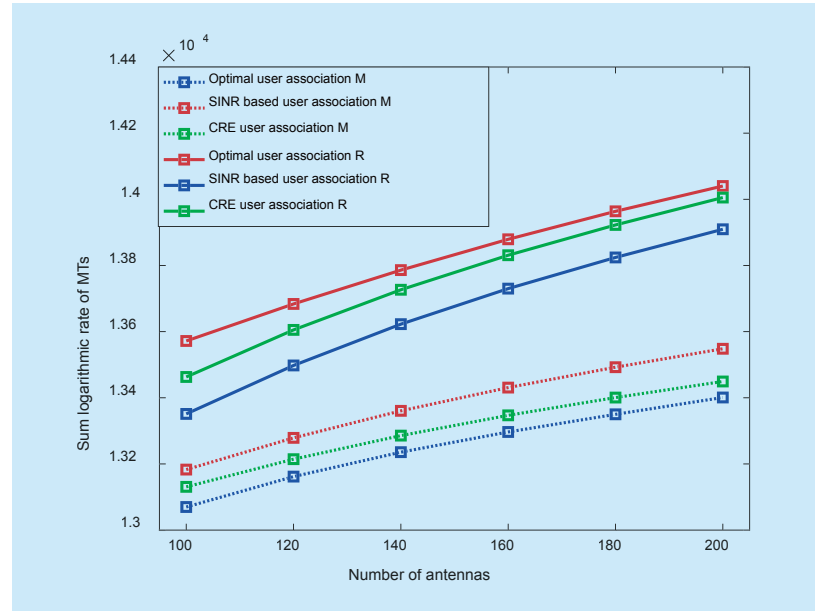


Fig. 8. Sum logarithmic rate varying with the increasing number of antennas.

is more obvious when the amount of users is very large, which means that the distributed optimization algorithm gives a more support to the large-scale users.

The user association situations both in the Manhattan urban and the open rural scenario with the distributed optimization algorithm are shown in figure 12 and figure 13. The number of user is set as 800 and the MBS is equipped with 100 antennas. In the Manhattan urban

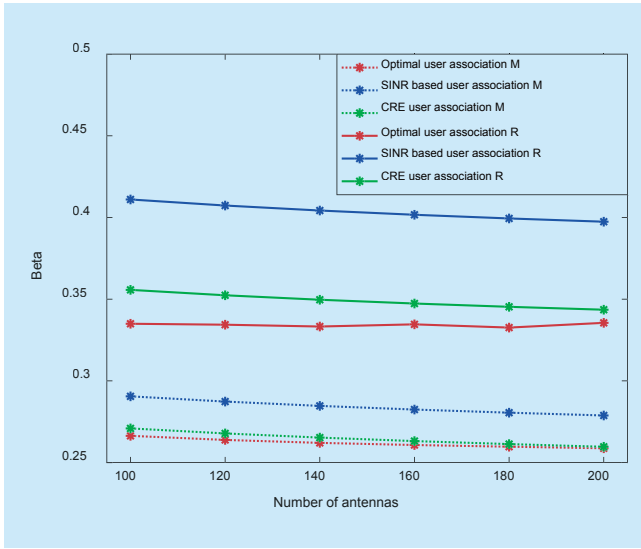


Fig. 9. The  $\beta$  varying with the increasing number of antennas.

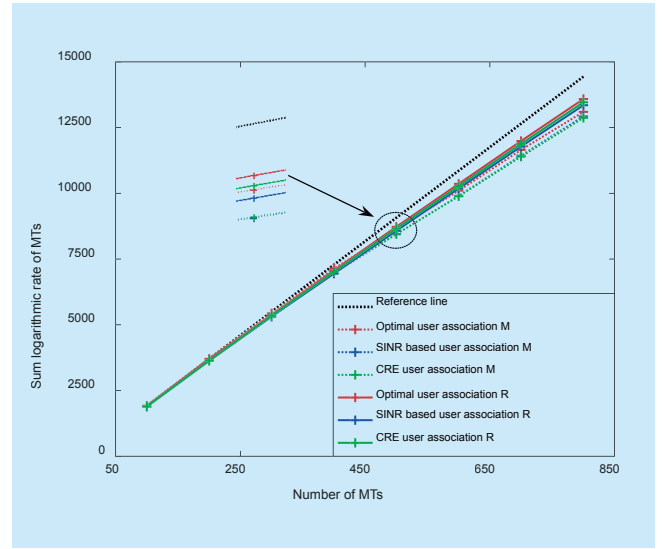


Fig. 10. Sum logarithmic rate varying with the increasing number of MTs.

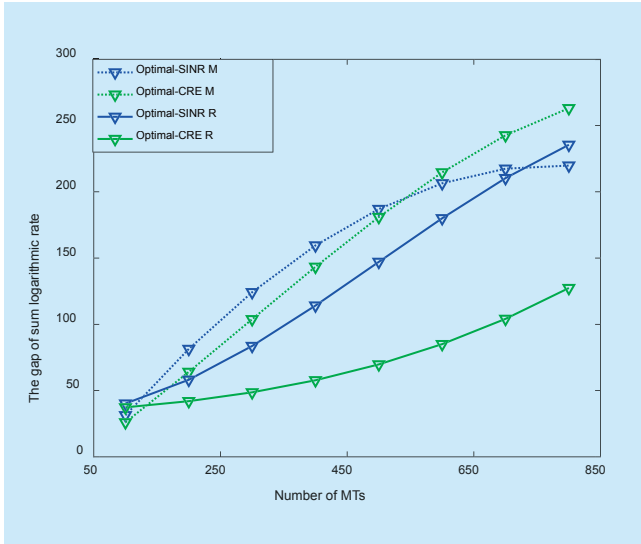


Fig. 11. Gap of the sum logarithmic rate between the distributed optimization method and the other two methods varying with the increasing number of MTs.

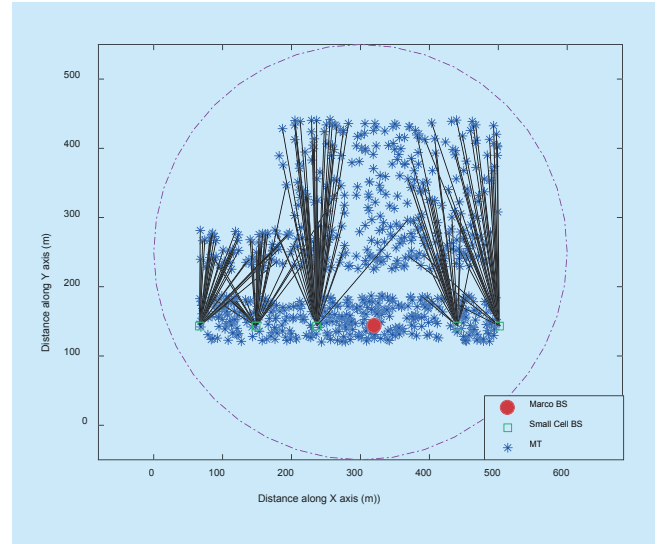


Fig. 12. Optimal user association in Manhattan urban.

scenario, we can find that 26.5% users in the north of buildings are associated with SBSs, but just 1.5% users in the street are associated with SBSs. This is because the deployment of SBSs introduced in Section 2.3. In this deployment, the users which are in NLOS transmission with MBS chose to associate with a close by SBS that can apply a good service. But in the rural scenario, due to the LOS environment, most users associate with MBS and only

15.25% users far from the MBS are associated with SBSs.

## V. CONCLUSION

This article proposes a scheme for solving the user association and wireless backhaul bandwidth allocation problem in a two-tier HetNet at the mmWave band. The closed-form expression of sum logarithmic user rate is es-

established according to the result of multi-user MIMO downlink employing ZFBF. Aiming at finding the optimal solutions of user association variable  $x_{j,i}$  and the wireless backhaul bandwidth allocation factor  $\beta$  to maximize the sum of logarithmic user rate, a distributed optimization algorithm is applied to solve the problem. The conclusion is drawn as follow. Firstly, the channel model generated by RT, which takes advantages of simulating the actual scene, is compared with 3GPP channel model. And it is verified that the RT channel model is equivalent to 3GPP channel model at 30 GHz. Secondly, simulation results reveal that 6% loads have been offloaded from the heavy-load MBS to the light-load SBSs with the SINR bias. Thirdly, by increasing the number of antenna array size of MBS, the sum of logarithmic user rate is logarithmically increased and the wireless backhaul bandwidth factor  $\beta$  is decreased owing to the beamforming gain. Simultaneously, by increasing the number of MTs, the sum of logarithmic user rate is linearly increased and the gap is getting wider between the distributed optimization algorithm and the SINR-based method as well as between the distributed optimization algorithm and the CRE method.

In order to promote this research, some ideas will be considered in the next work as: (1) Each small cell is allocated with a specific wireless backhaul bandwidth allocation factor  $\beta$  instead of unified bandwidth resource allocation. (2) Both MBS and SBS are equipped with large-scale antenna arrays. (3) Power optimization is added to the optimization problem.

## ACKNOWLEDGEMENTS

This work was supported by NSFC under Grant (61725101 and 61771036), the ZTE Corporation, State Key Lab of Rail Traffic Control and Safety Project under Grant (RCS2017ZZ004 and RCS2017ZT008), Beijing Natural Science Foundation under Grant L161009. The work of Ning Wang was sup-

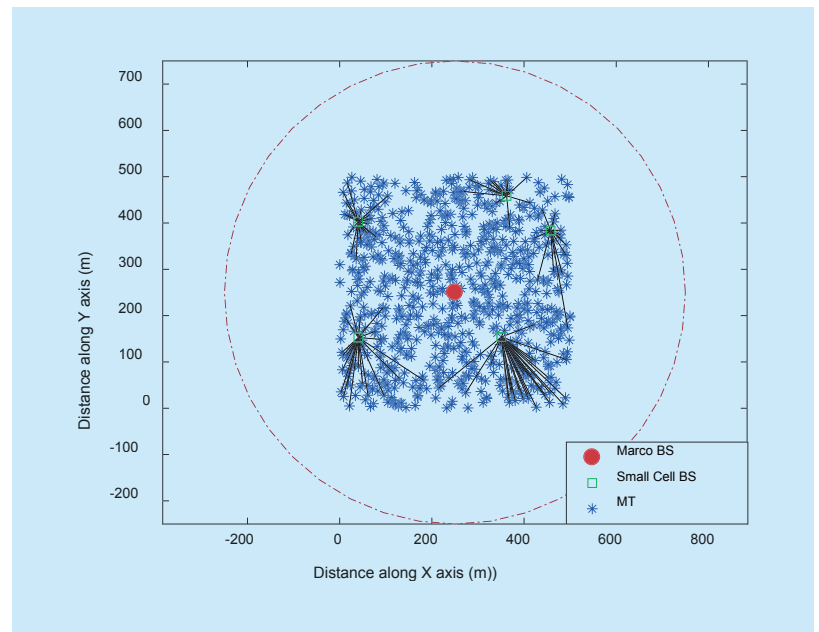


Fig. 13. Optimal user association in rural area.

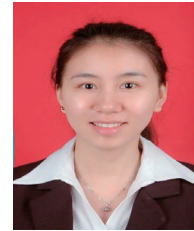
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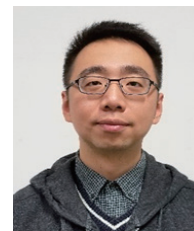
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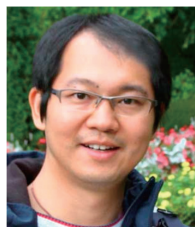


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