# Energy Efficient User Association and Power Allocation in Millimeter Wave Based Ultra Dense Networks with Energy Harvesting Base Stations

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Abstract-Millimeter wave (mmWave) communication technologies have recently emerged as an attractive solution to meet the exponentially increasing demand on mobile data traffic. Moreover, ultra dense networks (UDNs) combined with mmWave technology are expected to increase both energy efficiency and spectral efficiency. In this paper, user association and power allocation in mmWave based UDNs is considered with attention to load balance constraints, energy harvesting by base stations, user quality of service requirements, energy efficiency, and cross-tier interference limits. The joint user association and power optimization problem is modeled as a mixed-integer programming problem, which is then transformed into a convex optimization problem by relaxing the user association indicator and solved by Lagrangian dual decomposition. An iterative gradient user association and power allocation algorithm is proposed and shown to converge rapidly to an optimal point. The complexity of the proposed algorithm is analyzed and the effectiveness of the proposed scheme compared with existing methods is verified by simulations.

*Index Terms*—Ultra dense networks, millimeter wave, energy harvesting, heterogeneous networks, user association, power allocation, load-balancing, energy efficiency.

#### I. INTRODUCTION

The proliferation of network devices and the growing demand for network services are contributing to a dramatic increase in overall network data traffic. This problem is exacerbated in typical macrocell networks because of blind spots and shadowing. A promising solution is the deployment of ultra dense networks comprising flexibly deployed low-power small base stations (BSs), such as microcell BSs, picocell BSs and femtocell BSs [1]. In 5G [2], ultra dense networks that are deployed with low-cost and low-power small cells are expected to enhance the overall performance of the network in terms of energy efficiency and load balancing. The essence of

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Victor C. M. Leung is with the Department of Electrical and Computer Engineering, The University of British Columbia, Vancouver, BC, V6T 1Z4, Canada (e-mail: vleung@ece.ubc.ca). ultra dense cell deployment is to shorten the physical distance between the transmitter and the receiver, so as to improve the performance of the system. Compared to traditional networks, ultra dense networks have the following advantages: (1) small cells can be deployed by users, which significantly reduces the cost of deployment; (2) ultra dense cells have a flexible configuration, and can reduce interference and improve energy efficiency through the setting of intelligent rules; and (3) ultra dense networks can completely solve problem of blind spots and achieve the goal of load-balancing.

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However, in practice, due to the intensive characteristics of ultra dense deployment and the uncertainty of user deployment, radio resource allocation [3], user association and interference mitigation become extremely challenging. Because of the high deployment density, cross-tier interference from small cell to macrocell [4], local-tier interference from small cell to small cell, and the additive white Gaussian noise, cannot be ignored. These sources of interference can determine the association rule, as well as the power allocation policy between users and BSs. Under such circumstances, users are free to override the association's decisions to obtain a better payoff. On the other hand, the capacity of BSs has a limit, and thus we need to carefully consider these various elements in determining the association rules between users and BSs.

The millimeter wave (mmWave) frequency band is 30 ~ 300 GHz, corresponding to wavelengths from 10 to 1 mm [5]. Due to its physical properties, mmWave can effectively solve many problems of high-speed broadband wireless access, and thus it has a broad application potential in short distance communication, such as in ultra dense small cell networks. The attenuation of mmWave reaches its maximum values in the 60 GHz, 120 GHz and 180 GHz bands [6]. This means that the interference levels for these attenuation bands are much lower compared to the 2-3 GHz bands. Moreover, due to the large 60 GHz bandwidth, mmWave systems can provide a relatively high data rates [7]. These characteristics of mmWave can play an indispensable role in enhancing spectral efficiency and energy efficiency of ultra dense networks.

Load-balancing is a main factor influencing the performance of BSs in heterogeneous ultra dense networks. Due to the cross-tier interference and the various capabilities of BSs, although users are uniformly associated with BSs, the uneven power allocation leads to differences in user experience [8] [9]. Load awareness based user association was proposed in [10] and [11]. Traditionally, the signal-to-interference-plus-noise

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ratio (SINR) was utilized to determine whether a user should be associated with a given BS; however, this approach can lead to serious load-imbalance in the network. Load awareness transfers congested macrocells to lightly loaded small cells. Thus, although users are served by macrocells, they can make an association judgement and access a lightly loaded small cell.

Another important aspect of some ultra dense networks is the harvesting of energy from the radio-frequency (RF) environment to help power devices with limited energy resources [12] [13]. Notably, wireless signals can transmit information and energy simultaneously, which means that transmitters can not only transmit information, but can also provide energy to charge the batteries of other devices. This method, known as simultaneous wireless information and power transfer (SWIPT) is a promising paradigm for ultradense networks.

## A. Related Work

Many studies have addressed the problems of loadbalancing and user association. In [14], the authors proposed a proportional fairness scheme to solve the user association problem. The authors in [15] proposed a channel-access-aware association scheme in which the main idea is that each user estimates its channel access probability from different BSs to determine the best BS. Instead of calculating maximum SINR, this scheme gave preferential assignment to the lowpower small cells. A particular power allocation scheme was proposed in [16], which presented a transmission coordination model called ON-OFF transmission coordination which can control the BS to transmit either the maximum transmit power or none. References [17], [18] and [19] all present loadaware schemes in user association for cellular networks, which provide guarantees on load-balancing and quality of service (QoS) requirements.

There have also been a number of studies of SWIPT, including [20]-[23]. In [20] and [21], the authors investigated secure communication in SWIPT with eavesdroppers and multiple energy harvesting receivers. In [22], the authors studied the interference-aware resource allocation problem considering both time-switching and power-splitting approaches to SWIPT, in which interference signals were considered to improve the energy harvesting rate. Similarly, in [23], the authors proposed different resource allocation schemes in SWIPT that guarantee a minimum the energy harvesting rate. In this paper, we will consider a form of SWIPT in which densely deployed base stations can harvest energy from the transmissions of other base stations to end users in the network.

There has also been some progress on user association in mmWave networks. In [24], the authors provided a distributed approach that solved the joint association and relaying problem in mmWave networks. Auction-based resource allocation in 60 GHz mmWave networks was presented in [25]. The authors of [26] proposed the use of matching theory for managing the spectrum resources of a heterogeneous small cell backhaul network.

A goal of network design is to guarantee QoS in terms of user transmission rate. In [27] and [28], the authors propose the use of historical information about QoS to assist users in selecting BSs with better long-term QoS instead of those with better immediate QoS. The literature has also addressed user association and energy efficiency in wireless networks. In [29] and [30], the authors considered improving energy efficiency through base station sleeping technology. The authors in [31] proposed a distributed load-balancing algorithm for user association. In [32], the authors proposed a novel event data collection approach called reliability and multipath encounter routing (RMER), which can greatly reduce energy consumption in networks. However, to the best of the authors' knowledge, user association and power allocation in mmWave based ultra dense networks, by jointly considering loadbalancing constraints, QoS requirements, energy efficiency, energy harvesting by base stations, and cross-tier interference limits, have not been studied in previous works.

## B. Main Contributions

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

- Development of a novel energy efficient mmWave based ultra dense network optimization framework: This is a new approach to network optimization design based on the consideration of considering load-balancing constraints, QoS requirements, energy efficiency, energy harvesting by base stations, and cross-tier interference limits in mmWave based ultra dense networks.
- Formulation of a user association and power allocation problem with multiple constraints: We formulate the load-aware energy efficient user association and power optimization problem in mmWave based ultra dense network as a mixed-integer programming problem. Crosstier interference limits are used to protect the macrocells. A QoS requirement in terms of minimum achievable rate is provided to guarantee reliable transmissions.
- Proposal of load-aware energy efficient user association and power allocation algorithm: The formulated nonconvex problem is transformed into a convex optimization problem by relaxing the user association indicator and solved by Lagrangian dual decomposition. An iterative gradient user association and power allocation algorithm is proposed and is shown to converge to the optimal point quickly. The complexity of the proposed algorithm is analyzed and the effectiveness of the proposed scheme is verified by simulations comparing with existing method.
- Support of energy harvesting and quick convergence: Energy harvesting by base stations is considered in this paper. We also propose an iterative gradient method to update the transmit power variable and find an optimal association method for all users. We use the Newton-Raphson method to update the Lagrange multipliers and transmit power variable; it takes only a few iterations to converge towards an optimal point with guarantees on QoS and load-balancing. Theoretical analysis and simulation results verify the practicability and the feasibility of proposed method.
- Development of a load-aware scheme by using the logutility function under power control: a load-aware scheme



Fig. 1. Architecture of a mmWave based ultra dense small cell networks with energy harvesting base stations.

redistributes the traffic load to maximize the network utility and energy efficiency among BSs. Users tend to be attracted to macrocells with higher capacity for data transmission; the load-aware scheme reduces the priority of macrocells and redistributes the traffic selectively for all BSs so as to balance the load.

The rest of this paper is structured as follows. Section II introduces the system model, followed by a construction of the optimization problem formulation. Section III presents the Lagrangian dual decomposition formalism and an iterative gradient algorithm to find an optimal solution. Section IV includes an analysis of the performance of our proposed algorithms via simulations. Section V concludes this paper.

## **II. SYSTEM MODEL AND PROBLEM FORMULATION**

# A. System Model

As shown in Fig. 1, we consider a mmWave based ultra dense network, which consists of ultra dense small cells overlaid on one macrocell. We focus on the user association and transmit power allocation in the downlink of such a network. The set of all (macro and small) cells is denoted by  $\mathbb{B} \in \{1, 2, ..., B\}$ , and the set of distributed users is denoted by  $\mathbb{U} \in \{1, 2, ..., U\}$ . We assume that a user can be associate with only one BS,  $\{x_{ij}\}$  is used to indicate the association variable between user *i* and BS *j*. If user *i* is associated with BS *j*,  $x_{ij} = 1$ , otherwise  $x_{ij} = 0$ .

Let  $g_{ij}$  be the power gain from BS j to user i. In this paper, we use the Friis transmission equation [33] to model the power gain:

$$g_{ij} = \frac{g_{ij}^{IX} g_{ij}^{KX} \varsigma^2}{16\pi^2 \left(\frac{d_{ij}}{d_0}\right)^{\eta}} \tag{1}$$

where  $g_{ij}^{\text{Tx}}$  is the transmit antenna gain from BS j to user i,  $g_{ij}^{\text{Rx}}$  is the receive antenna gain from BS j to user i,  $\varsigma$  is the wavelength,  $d_{ij}$  is the distance from BS j to user i,  $d_0$  is the far field reference distance, and  $\eta$  is the path-loss exponent  $(\eta \in [2, 6])$ .

The SINR of user  $i \ (i \in \mathbb{U})$  receiving from the BS  $j \ (j \in \mathbb{B})$  can be written as

$$SINR_{ij} = \frac{p_{ij}g_{ij}}{\sum\limits_{k \in \mathbb{B}, k \neq j} p_{kj}g_{kj} + \sigma^2}$$
(2)

where  $p_{ij}$  is the transmit power from BS j to user i, W is the system bandwidth, and  $\sigma^2$  is the variance of additive white Gaussian noise (AWGN). According to Shannon's capacity formula, the achievable rate for user i from BS j is given by

$$c_{ij} = \frac{W}{K_j} \log_2 \left( 1 + SINR_{ij} \right), \forall j \in \mathbb{B},$$
(3)

where  $K_j$  is the total number of users associated with BS j, and thus each user can receive  $1/K_j$  of the total frequency band available. As noted above, we assume that each user can be associated with only one BS. Because it is more difficult to implement multiple-BS association than single-BS association, multiple-BS association will increase the solution complexity and is not effective in practical systems. Thus, we can use  $x_{ij}$ to be a binary variable to indicate whether user i is associated with BS j.

### B. Problem Formulation

Before modeling the problem, let us introduce the following constraints:

(1) User scheduling constraint: A user can be associated with only one BS at a time. Thus, we have<sup>1</sup>

$$\sum_{j} x_{ij} = 1, \ \forall i \in \mathbb{U}.$$
(4)

(2) Total power constraint:

$$\sum_{i} x_{ij} p_{ij} \leqslant p_{\max}, \ \forall j \in \mathbb{B}$$
(5)

where  $p_{\text{max}}$  denotes the maximum transmit power between user *i* and BS *j*.

(3) QoS constraint:

$$\sum_{j} x_{ij} c_{ij} \geqslant R_t, \ \forall i \in \mathbb{U}$$
(6)

where  $R_t$  denotes the minimum transmit data rate for each user to maintain its own achievable rate.

(4) Cross-tier interference constraint:

$$\sum_{i} \sum_{k \in \mathbb{B}, k \neq j} x_{ij} p_{kj} g_{kj} \leqslant I_j, \ \forall j \in \mathbb{B}$$
(7)

where  $I_j$  denotes the maximum interference constraint. This constraint can be interpreted as an effective interference coordination mechanism. According to differences in traffic load conditions of small cells in ultra dense networks, the system will adjust the interference coordination mechanism dynamically to improve the spectral efficiency/energy efficiency.

(5) Constraint on the number of associated users:

$$\sum_{i} x_{ij} = K_j, \ \forall j \in \mathbb{B}$$
where  $0 \leq K_j \leq N_U$ .
(8)

<sup>1</sup>Unless otherwise denoted, summations over the BS index j extend over all of B, and summations over the user index i extend over all of U. In order to maximize the network utility, we focus on the user association and resource allocation problem. Due to limited bandwidth, we assume that frequency resources are allocated for every associated user uniformly. In other words, we focus only on power allocation and user association to achieve load-balance and energy efficiency improvement.

During the process of user association with a BS, the issue of power consumption between the users and BSs needs to be considered. We also assume that each BS is equipped with an energy harvesting unit that can use received energy for replenishing a rechargeable battery. With this assumption, the net power consumption of the network is given by

$$U_P(X,P) = \sum_j p_{cj} + \sum_i \sum_j x_{ij} p_{ij}$$
  
$$-\psi \sum_i \sum_j \sum_{m \in B} x_{ij} p_{ij} |g_{jm}|^2$$
(9)

where  $X \triangleq [x_{ij}]_{\mathbb{U}\times\mathbb{B}}$  is the user association matrix;  $P \triangleq [p_{ij}]_{\mathbb{U}\times\mathbb{B}}$  is the power allocation matrix;  $\sum p_{cj}$  is the circuit power consumed by the BSs; the term  $\sum_{i}^{j} \sum_{j} x_{ij} p_{ij}$  is the total transmit power consumed by the BSs, which will be particularly affected by the user association problem; and  $\psi \sum_{m \in B} x_{ij} p_{ij} |g_{jm}|^2$  is the energy harvested by all BSs, where  $\psi$  is the coefficient of energy harvesting efficiency of the BSs.

So given the power consumption function, we can formulate the optimization problem of interest as follows:

$$\max_{X,P} \sum_{i} \sum_{j} x_{ij} \frac{\log\left(\frac{W \log_2(1+SINR_{ij})}{\sum_{k \in U} x_{kj}}\right)}{U_P(X,P)}$$
(10)

s.t.

$$C1: U_P(X, P) = \sum_{j} p_{cj} + \sum_{i} \sum_{j} x_{ij} p_{ij}$$
$$-\psi \sum_{i} \sum_{j} \sum_{m \in B} x_{ij} p_{ij} |g_{jm}|^2$$
$$C2: \sum_{j} x_{ij} = 1, \ \forall i \in \mathbb{U}$$
$$C3: \sum_{i} x_{ij} = K_j, \ \forall j \in \mathbb{B}$$
$$C4: \sum_{i} x_{ij} p_{ij} \leq p_{\max}, \ \forall j \in \mathbb{B}$$
$$C5: \sum_{j} x_{ij} c_{ij} \geq R_t, \ \forall i \in \mathbb{U}$$
$$C6: x_{ij} \geq 0, \ 0 \leq K_j \leq N_U \ \forall i \in \mathbb{U}, \ \text{and} \ \forall j \in \mathbb{B}$$
$$C7: \sum_{i} \sum_{k \in \mathbb{B}, k \neq j} x_{ij} p_{kj} g_{kj} \leq I_j, \ \forall j \in \mathbb{B}$$
(11)

where C1 is the total power consumption according to (9); C2 guarantees that each user can be associated with only one BS; C3 is the constraint that there are  $K_j$  users being served by BS j; C4 is the maximum transmit power limit of user i from BS j; C5 sets the QoS requirement  $R_t$  for user i to ensure its achievable rate; C6 specifies the ranges of  $x_{ij}$  and  $K_j$ ; and C7 is the cross-tier interference constraint.

# III. LAGRANGIAN DUAL DECOMPOSITION

In this section, we consider the solution to the optimization problem (10)-(11). This problem is a mixed-integer optimization problem, which has very high complexity due to the lack of convexity of the objective and the binary nature of the variables in X.. To address the latter problem, we relax these variables, and replace (10)-(11) with the following:

$$\max_{X,P} \sum_{i} \sum_{j} x_{ij} \frac{\log\left(\frac{W \log_2(1+SINR_{ij})}{\sum_{k \in U} x_{kj}}\right)}{U_P(X,P)}$$
(12)

s.t.

$$\begin{split} & -\psi \sum_{i}^{j} \sum_{j} \sum_{m \in B}^{i} x_{ij} p_{ij} |g_{jm}|^{2} \\ & C2: \sum_{j} x_{ij} = 1, \ \forall i \in \mathbb{U} \\ & C3: \sum_{i} x_{ij} = K_{j}, \ \forall j \in \mathbb{B} \\ & C4: \sum x_{ij} p_{ij} \leqslant p_{\max}, \ \forall j \in \mathbb{B} \end{split}$$

 $C1: U_P(X, P) = \sum p_{cj} + \sum \sum x_{ij} p_{ij}$ 

$$C4: \sum_{i} x_{ij} p_{ij} \leq p_{\max}, \ \forall j \in \mathbb{B}$$
  

$$C5: \sum_{j} x_{ij} c_{ij} \geq R_t, \ \forall i \in \mathbb{U}$$
  

$$C6: x_{ij} \geq 0, \ 0 \leq K_j \leq N_U \ \forall i \in \mathbb{U}, \ \text{and} \ \forall j \in \mathbb{B}$$
  

$$C7: \sum_{i} \sum_{k \in \mathbb{B}, k \neq j} x_{ij} p_{kj} g_{kj} \leq I_j, \ \forall j \in \mathbb{B}$$
  

$$C8: 0 \leq x_{ij} \leq 1, \ \forall i \in \mathbb{U}, \ \text{and} \ \forall j \in \mathbb{B}$$

(13)

We use the Lagrangian dual decomposition method to solve the relaxed problem (12)-(13). The corresponding Lagrangian function is given by

$$L(\{x_{ij}\},\{p_{ij}\},\mu,\lambda,\nu,\tau)$$

$$=\sum_{i\in\mathbb{U}}\sum_{j\in\mathbb{B}}x_{ij}\frac{\log\left(\frac{W\log_2(1+SINR_{ij})}{\sum_{k\in\mathbb{U}}x_{kj}}\right)}{U_P(X,P)} + \sum_{j\in\mathbb{B}}\mu_j\left(K_j - \sum_{i\in\mathbb{U}}x_{ij}\right)$$

$$+\sum_{j\in\mathbb{B}}\lambda_j\left(p_{\max} - \sum_{i\in\mathbb{U}}x_{ij}p_{ij}\right) + \sum_{i\in\mathbb{U}}\nu_i\left(\sum_{j\in\mathbb{B}}x_{ij}c_{ij} - R_t\right)$$

$$+\sum_{j\in\mathbb{B}}\tau_j\left(I_j - \sum_{i\in\mathbb{U}}\sum_{k\in\mathbb{B},k\neq j}x_{ij}p_{kj}g_{kj}\right)$$
(14)

where  $\mu = [\mu_1, \mu_2, ..., \mu_B]^T$ ,  $\lambda = [\lambda_1, \lambda_2, ..., \lambda_B]^T$ ,  $\nu = [\nu_1, \nu_2, ..., \nu_U]^T$  and  $\tau = [\tau_1, \tau_2, ..., \tau_B]^T$  are the Lagrange multipliers used to relax the coupled constraint. Thus, the Lagrangian dual function can be written as

$$D(\mu,\lambda,\nu,\tau) = \max_{X,P} L(\{x_{ij}\},\{p_{ij}\},\mu,\lambda,\nu,\tau), \quad (15)$$

and so the Lagrangian problem of (15) can be written as

$$\min_{\mu,\lambda,\nu} D(\mu,\lambda,\nu,\tau).$$
(16)

## A. Dual Decomposition

We divide the original problem into two independent subproblems through the Lagrangian dual method, so that we can solve this optimization problem by solving the two subproblems.

The problem (12) subject to the constraints (13) can be rewritten as

$$\max_{X,P} \left\{ \sum_{i} \sum_{j} x_{ij} \frac{\log \left[W \log_2 \left(1 + SINR_{ij}\right)\right]}{U_P\left(X,P\right)} \\ - \sum_{i} K_j \frac{\log \left(K_j\right)}{U_P\left(X,P\right)} \right\}$$
(17)

where we let the power consumption C1 be evenly distributed on both fractional sides. The dual problem using the Lagrangian dual decomposition method is given by

$$\min_{\mu,\lambda,\nu,\tau} D(\mu,\lambda,\nu,\tau) = f_{X,P}(\mu,\lambda,\nu,\tau) + g_{K,P}(\mu,\lambda,\nu,\tau)$$
(18)

where

$$f_{X,P}(\mu,\lambda,\nu,\tau) = \begin{cases} \sum_{i} \sum_{j} x_{ij} \frac{\log [W \log_2 (1 + SINR_{ij})]}{U_P(X,P)} \\ -\sum_{i} \sum_{j} x_{ij} (\mu_j + \lambda_j p_{ij} - \nu_i c_{ij}) \\ -\sum_{i} \sum_{j} x_{ij} \tau_j \sum_{k \in \mathbb{B}, k \neq j} p_{kj} g_{kj} \end{cases}$$

$$s.t. \sum_{j} x_{ij} = 1$$

$$0 \leqslant x_{ij} \leqslant 1$$

$$U_P(X,P) = \sum_{j} p_{cj} + \sum_{i} \sum_{j} x_{ij} p_{ij} \\ -\psi \sum_{i} \sum_{j} \sum_{m \in B} x_{ij} p_{ij} |g_{jm}|^2 \end{cases}$$

$$(19)$$

$$g_{K,P}(\mu,\lambda,\nu,\tau) = \begin{cases} \max_{K,p} \left\{ \sum_{j} \left( \mu_{j}K_{j} + \lambda_{j}p_{\max} - \sum_{i} \nu_{i}R_{t} + \tau_{j}I_{j} \right) \right\} \\ -\sum_{i} K_{j} \frac{\log(K_{j})}{U_{P}(X,P)} \\ \text{s.t. } K_{j} \leq N_{U} \\ U_{P}(X,P) = \sum_{j} p_{cj} + \sum_{i} \sum_{j} x_{ij}p_{ij} \\ -\psi \sum_{i} \sum_{j} \sum_{m \in B} x_{ij}p_{ij} |g_{jm}|^{2} \end{cases}$$

$$(20)$$

The optimization problems (17) and (18) are the problems with respect to (X, P) and  $(\mu, \lambda, \nu)$  respectively. Thus, the original problem in (12) under condition (13) is transformed into subproblems (19) and (20).

The partial derivative of the objective of (19) can be

expressed as

$$\frac{\partial f_{X,P}\left(\mu,\lambda,\nu,\tau\right)}{\partial x_{ij}} = \frac{\log\left[W \log_2\left(1+SINR_{ij}\right)\right]}{U_P\left(X,P\right)} - \mu_j - \lambda_j p_{ij} + \nu_i c_{ij} - \tau_j \sum_{k \in \mathbb{B}, k \neq j} p_{kj} g_{kj}$$
(21)

In order to achieve the maximum of (17), the maximizer  $\{x_{ij}\}$  of the subproblem (19) is defined as

$$x_{ij} = \begin{cases} 1, \ if \ j = j^* \\ 0, \ if \ j \neq j^* \end{cases}$$
(22)

where  $j^* =$ 

$$\arg\max_{j} \left( \frac{\log \left[W \log_{2} \left(1 + SINR_{ij}\right)\right]}{U_{P}\left(X,P\right)} - \lambda_{j}\left(t\right)p_{ij}\left(t\right) \\ -\mu_{j}\left(t\right) + \nu_{i}\left(t\right)c_{ij} - \tau_{j}\left(t\right)\sum_{k \in \mathbb{B}, k \neq j} p_{kj}\left(t\right)g_{kj}\right) \right)$$
(23)

At the kth inner iteration, (23) can be considered to be a judgement criterion for users to determine the best service or the highest network utility of the BS.

Similarly, we can obtain  $K_j$  from the partial derivative of (20):

$$K_j(t+1) = e^{\left[\mu_j(t) \cdot U_P^{(t)}(X,P) - 1\right]}$$
(24)

where  $K_j$  can be considered to be an optimum association scheme. That is, it can be used by BS j to choose the specific number of users with which to associate.

We use the subgradient method to update the Lagrange multipliers as follows [34]:

$$\mu_{j}(t+1) = \mu_{j}(t) - \delta_{1}(t) \cdot \left(K_{j}(t) - \sum_{i} x_{ij}(t)\right)$$
(25)

$$\lambda_{j}(t+1) = \lambda_{j}(t) - \delta_{2}(t) \cdot \left( p_{\max} - \sum_{i} x_{ij}(t) p_{ij}(t) \right)$$
(26)

$$\nu_{i}(t+1) = \nu_{i}(t) - \delta_{3}(t) \cdot \left(\sum_{j} x_{ij}(t) c_{ij} - R_{t}\right)$$
(27)

$$\tau_{j}(t+1) = \tau_{j}(t) - \delta_{4}(t) \cdot \left( I_{j} - \sum_{i} \sum_{k \in \mathbb{B}, k \neq j} x_{ij}(t) p_{kj}(t) g_{kj} \right)$$
(28)

where  $\delta_1(t)$ ,  $\delta_2(t)$ ,  $\delta_3(t)$  and  $\delta_4(t)$  are step sizes. By updating the Lagrange multipliers  $\mu_j(t)$ ,  $\lambda_j(t)$ ,  $\nu_i(t)$  and  $\tau_j(t)$  via (25)-(28), the dual problem will achieve the global optimum when the multipliers converge.

In fact, we can use the Lagrange multiplier  $\mu_j$  (the price of the BSs for users) to choose the best service through *the law of supply and demand*:  $K_j$  represents the best standard; if the service demand  $\sum_i x_{ij}(t)$  exceeds the supply  $K_j$ , that will lead to higher price  $\mu_j$  to balance the market supply and demand. The users compare the obtained payoff from different associated BSs to determine whether the BS j is suitable to associate with through the judgement scheme (25). In other cases, the price will be affected by the loads of the BSs. If a BS is overloaded, then it will have to increase its price.

## B. Energy Efficiency and Power Allocation

In this subsection, we use the Newton-Raphson method to solve the power optimization problem.

We can rewrite the Lagrangian function (14) to get the power optimization function as:

$$f(p_{ij}) = \sum_{i \in \mathbb{U}} \sum_{j \in \mathbb{B}} x_{ij} \frac{\log_e \left(\frac{\log_2(1+SINR)}{K_j}\right)}{p_{cj} + \left(1 - \sum_{m \in B} \psi \cdot x_{ij} |g_{jm}|^2\right) \cdot p_{ij}} + \sum_{j \in \mathbb{B}} \lambda_j \left(p_{\max} - \sum_{i \in \mathbb{U}} x_{ij} p_{ij}\right).$$
(29)

We assume user i associates with BS j. Therefore, under the joint association,  $x_{ij}$  can be regarded as a constant value of 1. Then, the first-order partial derivative and the second derivative of the power function (29) are given by (30) and (31) at the top of next page.

Due to computational complexity of introducing the Hessian matrix, we focus only on the two-dimensional case.

In this case, the variable  $p_{ij}$  is updated as follows:

$$p_{ij}(t+1) = p_{ij}(t) + \delta_4(t) \Delta p_{ij}.$$
 (32)

where  $\delta_4(t)$  is the step size, and  $\Delta p_{ij}$  is given by

$$\Delta p_{ij} = \left| \frac{\partial f}{\partial p_{ij}} \right| / \left| \frac{\partial^2 f}{\partial p_{ij^2}} \right|$$
(33)

From the QoS constraint (6), we can obtain the minimum transmit power as

$$\widetilde{p}_{ij} = \frac{I_{ij}}{g_{ij}} \left( 2^{Rt} - 1 \right)$$
If  $p_{ij} < \widetilde{p}_{ij}$ , then  $p_{ij} = \widetilde{p}_{ij}$ .
(34)

By updating the transmit power variable, the value of the net power consumption is also changed. This is how we control the power variable to influence the user association scheme. Once we update the power control formula to reach convergence, the communication system will achieve a nearoptimal load balancing situation. At this moment, we define the user association scheme as load-aware association, which can transfer the traffic from a congested macrocell to relatively low-load or lightly loaded small cells. Thus, during the next trading time, the almost overloaded BSs will change their prices to reduce the number of associated users. And users will re-select objects based on the prices of the BSs. This load-aware association scheme is superior to SINR-based association. In the SINR-based algorithm, the BS overload problem is not considered.

#### C. Iterative Gradient Algorithm

In this subsection, we propose an iterative gradient algorithm to find the optimal user association solution.

This algorithm is shown as Algorithm 1, which solves the association problem (12) under the constraints in (13). In updating the variable  $p_{ij}$ , we use Newton's method which has

## Algorithm 1 Iterative Gradient Algorithm

1: Initialization:  $I_{\text{max}}$  and  $p_{\text{max}}$ , Let  $p_{ij} = p_0$ 

2: Initialization: Set the Lagrange multipliers  $\mu_j$ ,  $\lambda_j$  and  $\nu_i$  to zero

3: Set i = 0

4: repeat

10:

11: 12:

13:

14:

15:

16:

17:

User association 5:

for i = 1 to U do 6:

7: for j = 1 to  $\mathbb{B}$  do

(1) Calculate the power consumption  $U_P(P, X)$  accord-8: ing to (9): 9:

(2) Calculate  $j^*$  according to (23);

(3) Use the  $j^*$  to update  $x_{ij}$  according to (22);

(4) Update  $\mu_j$  according to (25);

(5) Update  $\lambda_j$  according to (26);

(6) Update  $\nu_i$  according to (27);

(7) Update  $\tau_i$  according to (28);

end for end for

Power allocation

18: for i = 1 to U do for j = 1 to  $\mathbb{B}$  do

19: (1) Calculate  $\frac{\partial f}{\partial p_{ij}}$  and  $\frac{\partial^2 f}{\partial p_{ij^2}}$ ; (2) Update  $\Delta p_{ij}$  according to (32), find the optimal step 20: 21: size  $\delta_4(t)$  according to [35]; 22: (3)  $p_{ij}(t+1) = p_{ij}(t) + \delta_4(t) \Delta p_{ij};$ if  $p_{ij} < \widecheck{p}_{ij}$  do then 23:  $p_{ij} = \widecheck{p}_{ij};$ 24: 25: end if if  $\sum x_{ij}p_{ij} < p_{\max}, \ \forall j \in \mathbb{B}$  do then 26: 27:  $\dot{p}_{ij} = p_{\max};$ 28: end if 29. Update  $p_{ij}$ ; end for

30: 31: end for

32: **until** Convergence or  $i = I_{max}$ ;

a relatively fast convergence rate. Algorithm 1, by firstly fixing the power variable  $p_{ij}$  to update the Lagrange multipliers and then updating the power variable  $p_{ij}$ , is feasible for practical use.

#### D. Complexity Analysis

In this subsection, we analyze the complexity of the proposed gradient algorithm. In Algorithm 1, the association scheme needs  $o(B \times U)$  operations to establish the associated relationship between users and BSs at each iteration, and power allocation also need  $o(B \times U)$  operations. We suppose that the optimal solution to the problem (12) requires I iterations to converge. All users at each iteration will receive price lists of all BSs and the communication service package (23) from the base stations. Then they will choose one of the BSs to associate with, which can guarantee their minimum rates. From the BS perspective, the BS will update the price list  $\mu_i$  according to the standard of achievable rates for users and load-balancing. Each of the Lagrange multipliers  $\mu_i$ ,  $\lambda_i$  and  $\tau_i$  require o(B) operations, and  $\nu_i$  requires o(U) operations. So the complexity of Algorithm 1 is o(I(2BU+3B+U)).

$$\frac{\partial f}{\partial p_{ij}} = \sum_{i \in \mathbb{U}} \sum_{j \in \mathbb{B}} \frac{SINR\left(p_{cj} + \left(1 - \sum_{m \in B} \psi x_{ij} |g_{jm}|^2\right) p_{ij}\right)}{\ln 2\left(p_{cj} + \left(1 - \sum_{m \in B} \psi x_{ij} |g_{jm}|^2\right) p_{ij}\right)^2} \cdot \frac{1}{p_{ij}(1 + SINR)\log_2(1 + SINR)} - \sum_{i \in \mathbb{U}} \sum_{j \in \mathbb{B}} \frac{\left(1 - \sum_{m \in B} \psi x_{ij} |g_{jm}|^2\right) \log_e\left(\frac{\log_2(1 + SINR)}{K_j}\right)}{\left(p_{cj} + \left(1 - \sum_{m \in B} \psi x_{ij} |g_{jm}|^2\right) p_{ij}\right)^2} - \sum_{j \in \mathbb{B}} \lambda_j$$

$$(30)$$

$$\frac{\partial^{2} f}{\partial p_{ij}^{2}} = \sum_{i \in \mathbb{U}} \sum_{j \in \mathbb{B}} \frac{SINR}{\left(p_{cj} + \left(1 - \sum_{m \in B} \psi \cdot x_{ij} |g_{jm}|^{2}\right) p_{ij}\right) p_{ij} \ln 2} \cdot \frac{-SINR \cdot (1 + \ln 2 \cdot \log_{2} (1 + SINR))}{\ln 2 \cdot p_{ij} (1 + SINR)^{2} (\log_{2} (1 + SINR))^{2}} \\
- \sum_{i \in \mathbb{U}} \sum_{j \in \mathbb{B}} \frac{SINR}{\left(p_{cj} + \left(1 - \sum_{m \in B} \psi \cdot x_{ij} |g_{jm}|^{2}\right) p_{ij}\right) p_{ij} \ln 2} \cdot \frac{SINR \cdot \left(1 - \sum_{m \in B} \psi \cdot x_{ij} |g_{jm}|^{2}\right)}{\ln 2 \cdot p_{ij} (1 + SINR) \log_{2} (1 + SINR)} \\
- \sum_{i \in \mathbb{U}} \sum_{j \in \mathbb{B}} \frac{2\left(1 - \sum_{m \in B} \psi \cdot x_{ij} |g_{jm}|^{2}\right) \cdot p_{ij}\right)^{3}}{\left(p_{cj} + \left(1 - \sum_{m \in B} \psi \cdot x_{ij} |g_{jm}|^{2}\right) \cdot p_{ij}\right)^{3}} \cdot \frac{SINR \cdot \left(p_{cj} + \left(1 - \sum_{m \in B} \psi \cdot x_{ij} |g_{jm}|^{2}\right) \cdot p_{ij}\right)}{\ln 2 \cdot p_{ij} (1 + SINR) \log_{2} (1 + SINR)} \\
- \sum_{i \in \mathbb{U}} \sum_{j \in \mathbb{B}} \frac{2\left(1 - \sum_{m \in B} \psi \cdot x_{ij} |g_{jm}|^{2}\right) \cdot p_{ij}\right)^{3}}{\left(p_{cj} + \left(1 - \sum_{m \in B} \psi \cdot x_{ij} |g_{jm}|^{2}\right) \cdot p_{ij}\right)^{3}} \cdot \left(1 - \sum_{m \in B} \psi \cdot x_{ij} |g_{jm}|^{2}\right) \cdot \log_{e} \left(\frac{\log_{2} (1 + SINR)}{K_{j}}\right)$$
(31)

#### IV. SIMULATION RESULTS AND DISCUSSION

In this section, we compare our proposed gradient algorithm with the MAX-SINR association algorithm by analyzing their performance via simulation. We consider an ultra dense network and all users are uniformly distributed within one macro cell. We set the deployed densities of small cells and users as  $\{\lambda_B, \lambda_U\} = \{1500, 6000\}$  per macrocell. The radius of the macrocell is 100 m. The additive white Gaussian noise power is set as  $\sigma^2 = kTB = -134$ dBm. The maximum transmitting power of the macrocell is set at 9.5 dBm, and the maximum transmitting powers of the small cells are all set at 4.7 dBm. We set  $\varsigma = 5$  mm,  $d_0 = 1$  m and W = 1200 MHz. Moreover, for all  $i \in \mathbb{U}, j \in \mathbb{B}$ , we set  $p_{ij} = p_0 = 0.1$ mW and  $g_{ij}^{Tx} = g_{ij}^{Rx} = 1$ . Finally, we set the energy harvester efficiency as  $\psi = 0.8$ .

Fig. 2 compares the number of users served by the macrocell and each small cell under different association schemes. The MAX-SINR association scheme shows that many users will be associated with the macrocell and it leads to a seriously unbalanced load, since the macrocell has a higher transmit power. By contrast, our proposed gradient algorithm promotes a load-balancing and energy-efficient association scheme. The proportions of users associated with the macrocell and each small cell are equal under our proposed algorithm. This reduces the macrocell load pressure and transfers congested users to a lightly loaded small cell in order to improve the overall network's energy efficiency.

Fig. 3 and Fig. 4 consider performance from the user perspective and small cell perspective, respectively, to compare



Fig. 2. The numbers of users associated with the macrocell and with each small cell under different association algorithms.

the energy efficiency of the two different algorithms. From the Fig. 3, under our proposed algorithm, the range of energy efficiency of users is mostly distributed between  $0.5 \times 10^{15}$  and  $3 \times 10^{15}$  bits/Joule. However, the range of energy efficiency of users under the MAX-SINR algorithm is from  $0.3 \times 10^{14}$ to  $1.8 \times 10^{14}$  bits/Joule. From this numerical comparison, it is concluded that the energy efficiency of users resulting from our proposed algorithm is 10 times that of the MAX-SINR algorithm. Fig. 4 shows that the sum of energy efficiency



Fig. 3. Cumulative distribution function of energy efficiency of users



Fig. 4. The accumulation of energy efficiency

achieved by our gradient algorithm is also almost 10 times that of the MAX-SINR association algorithm. Because the load capacity of each base station is limited, our algorithm seeks to maximize the energy efficiency [39] through coordinating the relationship between the system load and user's minimum service rate [40]. However, the MAX-SINR algorithm aims to maximize the user rate regardless of the load-balancing and energy efficiency, and for this reason, it will not usually attain a high rate of energy efficiency. So we can conclude that our proposed gradient method improves significantly in energy efficiency compared to the MAX-SINR method.

Fig. 5 shows the convergence behavior of energy efficiency of the two association schemes. We use Newton's method, which has a satisfactory convergence rate, to solve the problem (12) under constraints (13). From Fig. 5, we can draw an obvious conclusion that the proposed gradient based user association method requires approximately 20 iterations to reach the optimal point, but the MAX-SINR method requires approximately 35 iterations to find its optimal solution. Moreover, from Fig. 5, we see that for the gradient method the energy efficiency, or utility of power, is higher compared with the MAX-SINR method at each iteration. Moreover, as the number of iterations increases, the energy efficiency of the



Fig. 5. Convergence behavior of energy efficiency.

MAX-SINR algorithm is gradually reduced. So our proposed algorithm can not only achieve a near-optimal point, but it can also provide a load-balancing property in order to maximize the network utility under the power control constraint and QoS requirements. As the load aware association scheme addresses the network's energy efficiency, according to [36], to maximize the network's energy efficiency, it tends to lead to proportional fairness. This means that reducing the macrocell power consumption facilitates load-balancing and higher energy efficiency.



Fig. 6. CDFs of user rates under different user association schemes.

Fig. 6 shows the cumulative distribution functions (CDFs) of user long-term rates of the two association schemes. We set the QoS constraint  $R_t$  to 1 bps/Hz for both the proposed algorithm and MAX-SINR algorithm. User rates for MAX-SINR association range from  $2.9 \times 10^{10}$  to  $3.4 \times 10^{10}$  bits/s/Hz, but most of the achievable rates for users range from  $6.44 \times 10^9$  to  $6.48 \times 10^9$  bits/s/Hz in our proposed algorithm. The MAX-SINR algorithm is effective in enhancing the user rate. But the gap between user rates of the two algorithms is not that dramatic. And the rate that we get from our proposed algorithm satisfies the minimal user rate.

posed algorithm can provide users with a relatively constant value, which means that the pricing rules of all base stations (including the macro base station) are similar and constant. All users in this network can find the optimal associated base station that satisfies their minimal user rate and offers a reasonable price. Thus, this approach solves the problems of the limitation of macrocell traffic load and the existence of blind spots in the macrocell. The macrocell cannot provide an ideal achievable rate for all users. So an ultra dense network together with our proposed algorithm solves these problems.



Fig. 7. Energy efficiency versus the mmWave small cell antenna gain.

We now consider the blockage effect in the mmWave channel model. According to [37], we have correspondingly corrected the path loss as  $PL(d) = 20\log_{10}\left(\frac{4\pi d_0}{\varsigma}\right) + 10\eta\log_{10}\left(\frac{d}{d_0}\right) + \sigma^2$ . A simple yet accurate channel model is applied for simplifying blockage modeling according to [38], where a user within a certain distance from a BS is considered to be in line-of-sight (LOS) contact and beyond that distance is assumed to be in non-line-of-sight (NLOS) contact. The LOS and NLOS path loss exponents for BS-to-user are set as 2 and 3.4, respectively, and the LOS and NLOS path loss exponents for BS-to-BS are set as 2 and 3.5, respectively. The LOS and NLOS shadowing factors for BS-to-user are set as 5.9 and 7.6, respectively, and the LOS and NLOS shadowing factors for BS-to-BS are set as 6.5 and 7.9, respectively.

Fig. 7 shows the antenna (omni-directional) gain's effects on the energy efficiency when considering blockage in the mmWave channel model. As can be seen in Fig. 7, our proposed algorithm has higher energy efficiency than the MAX-SINR algorithm in this case as well provides more energy efficiency than MAX-SINR algorithm.

Fig. 8 shows the accumulation of energy efficiency from the small cell perspective when the antenna gain is set as 13 dBi. As the number of base stations increases, the accumulation of energy efficiency also increases. As can be seen from the figure, when the number of base stations is 1500, our proposed algorithm's energy efficiency is about 9 times that of the traditional MAX-SINR algorithm. Therefore, even with blockage taken into consideration, our proposed algorithm still has significant advantage in achieving energy efficiency.



Fig. 8. The accumulation of energy efficiency considering the blockage effect in the mmWave channel for the two algorithms.



Fig. 9. Convergence behavior of energy efficiency with blockage effect in the mmWave channel model for the two algorithms.

Fig. 9 shows the convergence behavior of energy efficiency of the two user association schemes when considering the blockage effect. It shows that our proposed algorithm still converges rapidly. Our proposed algorithm requires approximately 20 iterations to converge, while the energy efficiency curve of the MAX-SINR algorithm seems to not convergence due to its neglect of load balancing.

## V. CONCLUSION

In this paper, we have considered a mmWave based ultra dense network, which also combines energy harvesting at base stations. We have proposed an effective interference coordination mechanism to cognitively limit the interference between the BSs and users in ultra dense networks. Moreover, we have modeled a network utility optimal function under constraints on power and QoS. We have also proposed a gradient association technique to solve this optimization problem, which has a satisfactory convergence rate and can find a nearoptimal solution. By using Lagrangian dual decomposition, the dual optimization problem can be decoupled into two subproblems, which can be solved separately.

The simulation results show that our algorithm outperforms the MAX-SINR algorithm. The numerical results demonstrate that load-balancing association and price control user association significantly improve the network utility and energy efficiency, and it also provides a satisfactory user experience in pricing rules and user rate under the minimal user rate constraint.

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