Energy Efficiency in QoS Constrained 60 GHz Millimeter-Wave Ultra-Dense Networks

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Abstract. Millimeter-Wave (mmWave) communication in ultra-dense networks (UDNs) has been considered as a promising technology for future wireless communication systems. Exploiting the benefits of mmWave and UDNs, we introduce a new approach for jointly optimizing small-cell base station (SBS) - user (UE) association and power allocation to maximize the system energy efficiency (EE) while guaranteeing the quality of service (QoS) constraints for each UE. The SBS-UE association problem poses a new challenge since it reflects as a complex mixed-integer non-convex problem. On the other hand, the power allocation problem is in non-convexity structure, which is impossible to handle with the association problem concurrently. An alternating descent method is thus introduced to divide the primal optimization problem into two sub-problems and handle one-by-one at each iteration, where the SBS-UE association problem is reformulated using the penalty approach. Then, path-following algorithms are developed to convert non-convex problem into the simple convex quadratic functions at each iteration. Numerical results are provided to demonstrate the convergence and low-complexity of our proposed schemes.

Keywords: Millimeter-Wave · mmWave · Ultra-dense networks · Energy efficiency · User association · Power allocation · Penalty · Successive convex programming

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1 Introduction

Ultra-dense networks (UDNs) by deploying multiple small-cells base stations (SBSs) such as micro-cells, pico-cells, micro-cell operators[1] distributed in the traditional cell have been emerged as a promising technology to improve the coverage and network performance [3]. In UDNs, the processing load can be effectively shared among SBSs instead of centralizing at the traditional macro base stations. However, due to the limited capacity and the scheduling scheme, such deployed SBSs are not able to serve a large number of users (UEs) simultaneously. Thus, the SBS-UE association problem becomes very important [15].

Due to the rapid shifting of high-speed broadband wireless access, the application of Gigabit services such as real-time streaming, gigabyte file transfer have been broadly developed [1,11]. The core of such services is mainly based on millimeter-Wave (mmWave) communication, which is one of the powerful technologies enabling the high data rate services [4,17]. Such mmWave technologies utilize the frequency band from 30 to 300 GHz, which corresponds to wavelengths from 10 to 1 mm [6]. It has been reported that the maximum attenuation of mmWave can achieve in the 60 GHz, 120 GHz, 180 GHz frequency bands [19].

The application of mmWave in UDNs has been widely studied to exploit the benefits of short-range communication to the high data-rate services [1,20]. In particular, the UE association schemes have been developed to improve the load balancing in the UDNs [18,20]. The resource allocation schemes were also investigated since the wireless channels in the mmWave network are strongly unstable due to high frequency operation [14]. In the extending mmWave investigation, the joint optimization for both UE association and power allocation has taken into account [20]. The binary association problem in those schemes is usually applied with the relaxation method, then using the traditional Lagrangian and gradient methods [20]. For those previous works, the problem will become very challenging when more UEs join in the system. Thus, the local optimum is difficult to achieve, which produces high-complexity with large iterations for convergence.

In this paper, a new approach for jointly optimizing the SBS-UE association and power allocation is investigated. The energy efficiency (EE) of the whole networks is taken into account subject to the quality of service (QoS) requirements of each UE. Since the proposed SBS-UE association problem is a challenging mixed integer non-convex optimization problem, which poses a high complexity for large-scale networks. On the other hand, the association problem and non-convex power allocation problem have a close connection. Therefore, solving them concurrently is extremely infeasible. Following from the proposed algorithms in [2], it has proved the effectiveness in the large-scale UDNs with low computational complexity. Particularly, an alternating descent method is first derived, which allows us to divide the primal problem into two separated

[1] The term "micro-cell operator" is used to indicate the deployment of micro-cell base stations at the private areas like school zones, factories, company buildings with their individual policies [5].

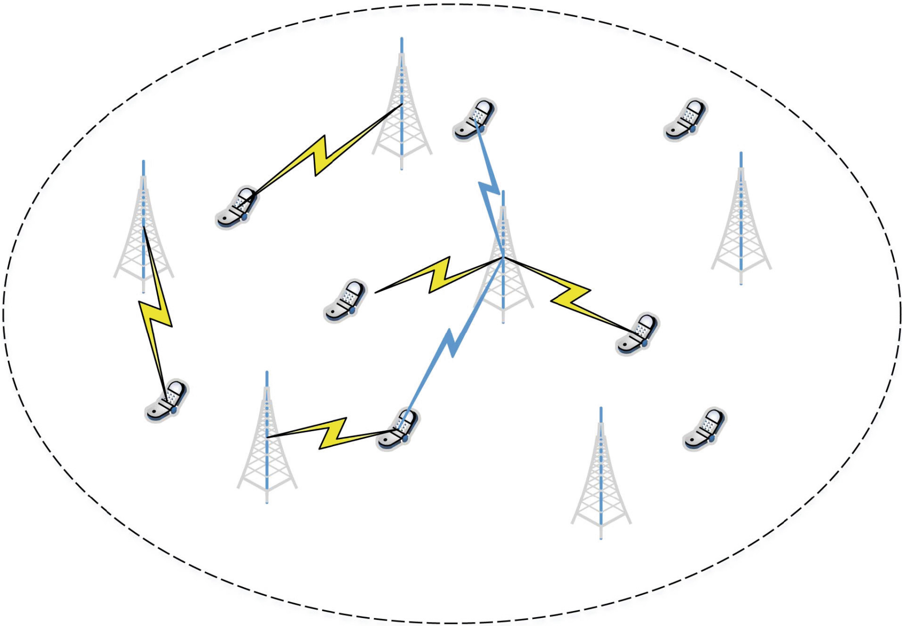

Fig. 1. The dense network scenario with M small-cell BSs and K users randomly distributed in the circular cell.

subproblems for easy to handle at the same time scale. Even though the association problem and power allocation problem are decoupled, their structures are still nonconvexity. The penalty method [15] is thus introduced, which relaxes those binary variables and force its square converting to its own original form. Then, the path-following procedures are employed to achieve computational low-complexity algorithms by converting the non-convex problem into the simple quadratic convex optimization problem [10,13,15]. Numerical results are thus developed to verify the convergence and effectiveness of our proposed algorithms.

Notation: Boldfaced symbols are used for optimization variables whereas non-boldfaced symbols are for deterministic terms, regardless of whether they are vectors or scalar values.

2 System Model and Problem Formulations

2.1 System Model

Consider the UDN consists of the set of M SBSs using 60-GHz mmWave band, $m \in \mathcal{M} \triangleq \{1, \ldots, M\}$ communicating with the set of K UEs, $k \in \mathcal{K} \triangleq \{1, \ldots, K\}$, where those locations are randomly distributed in the circular cell with radius $\mathcal{R}$, as shown in Fig. 1. All SBSs and UEs are equipped with single-antenna and operate in half-duplex mode. Since the 60-GHz frequency band is studied, the channel gain between SBS m and UE k is modeled as the Friis transmission equation [8]

$$g_{m,k} = \frac{l_{m,k}^{Tx} l_{m,k}^{Rx} \xi^2}{16\pi^2 (\frac{d_{mk}}{d_0})^\eta}, \tag{1}$$

where $l_{m,k}^{Tx}$ is the transmit antenna gain from SBS m to UE k, $l_{m,k}^{Rx}$ is the receive antenna gain from SBS m to UE k, ξ is the wavelength, d_{mk} is the distance between SBS m and UE k, d_0 is the far field reference distance, and η is the path-loss exponent ($\eta \in [2, 6]$).

Without loss of generality, we assume that each UE can associate only one SBS at each interval time and each SBS can serve multiple UEs by performing scheduling algorithms to avoid intra-cell interferences [7]. There are two main reasons for proposing the association problem. Firstly, the UEs can select the nearest SBS or the associated SBS with the best channel gain such that their minimum transmission rates are guaranteed. Secondly, the load-balancing of the whole systems can be improved, where the processing load is equally shared among SBSs.

Let us define $\mathbf{x} \triangleq [\mathbf{x}_1, \ldots, \mathbf{x}_M]^T$, $\mathbf{x}_m \triangleq [\mathbf{x}_{m,1}, \ldots, \mathbf{x}_{m,K}]^T$, where $\mathbf{x}_{m,k} \in \{0, 1\}$ is the association variable expressed as follow

$$\mathbf{x}_{m,k} = \begin{cases} 1 \text{ if UE } k \text{ associates with SBS } m, \\ 0 \text{ otherwise.} \end{cases}$$

Due to transmission scheduling among UEs at the associated SBS m, each UE will be assigned one time slot equal to another UEs. According to Shannon's capacity formula, the achievable rate for UE k via SBS m is given by

$$\begin{aligned} \mathcal{R}_{m,k}(\mathbf{x}, \mathbf{p}) &= \frac{W}{\mathcal{K}_m(\mathbf{x})} \log_2(1 + \gamma_{m,k}) \\ &= \frac{W}{\mathcal{K}_m(\mathbf{x})} \log_2 \left(1 + \frac{\mathbf{p}_m g_{m,k}}{\sum\limits_{n \in \mathcal{M} \setminus \{m\}} \mathbf{p}_n g_{n,k} + \sigma_m^2} \right), \end{aligned} \tag{2}$$

where W is the total bandwidth, $\mathbf{p}_m$ is the transmit power of SBS m, σ_m^2 is the variance of additive white Gaussian noise (AWGN), $\mathcal{K}_m(\mathbf{x}) = \sum_{k=1}^{K} \mathbf{x}_{m,k}$ is the number of UEs associated with SBS m. As seen from (2), UE k is subjected to the inter-cell interferences from other SBSs $n \neq m$.

2.2 Problem Formulations

Our objectives aim to maximize the EE maximization problem in terms of number of bits delivered per unit of Joule subject to the QoS rate threshold for each UE. The EE maximization problem can be expressed as [20].

$$\max_{\mathbf{x},\mathbf{p}} \mathcal{P}_1(\mathbf{x},\mathbf{p}) \triangleq \frac{\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} \mathbf{x}_{m,k}\mathcal{R}_{m,k}(\mathbf{x},\mathbf{p})}{\sum_{m\in\mathcal{M}} \mathbf{p}_m + p_{non}}, \quad (3a)$$

$$\text{s.t} \quad \sum_{m=1}^{M} \mathbf{x}_{m,k} = 1, \forall k \in \mathcal{K}, \quad (3b)$$

$$\mathbf{x}_{m,k} \in \{0,1\}, \forall m \in \mathcal{M}, k \in \mathcal{K}, \quad (3c)$$

$$0 \le \mathbf{p}_m \le \mathcal{P}_m^{max}, \forall m \in \mathcal{M}, k \in \mathcal{K}, \quad (3d)$$

$$\sum_{m\in\mathcal{M}} \mathbf{x}_{m,k}\mathcal{R}_{m,k}(\mathbf{x},\mathbf{p}) \ge \mathcal{R}_k^{min}, \forall k \in \mathcal{K}, \quad (3e)$$

where $p_{non} = M * p_a$ is the non-transmit power with p_a is the antenna circuit power. Constraint (3b) ensures that each UE must associate to one SBS while the constraint (3d) indicates the maximum transmit power of each SBS, and constraint (3e) guarantees the achievable rate of each UE must higher than the QoS requirement.

It can be observed from (3) that the objective function comprises of a difficult class of mixed-integer problem together with non-convex power allocation problem, which is a very challenging optimization problem. On the other hand, constraint (3e) also has nonconvexity structure. Therefore, dealing with binary association variable $\mathbf{x}$ and continuous transmit power variables $\mathbf{p}$ concurrently is infeasible. Especially at the large-scale networks, solving the association problem becomes more challenging. From the following, we introduce alternating descent algorithm, which allows us to divide the primal problem into two subproblems and handle one-by-one at the same time scale. In addition, the path-following methods with low-complexity are developed to convert non-convex problem into the simple quadratic convex problem at each iteration.

3 Alternating Descent Algorithm for Energy Efficiency Optimization Problem

In this section, we provide an approach to deal with those challenges in solving the problem (3). First of all, it can be observed that the binary constraint (3c) is a discrete variable. So finding the binary solution at the large scale networks takes very high-complexity and may increase in an exponential manner. Therefore, heuristic schemes such as binary search or exhaustive search seem infeasible to apply in this scenario. Tackling this issue, our aims are not only dealing with the binary in reasonable complexity but also focusing on high dimension networks. Following from [2,15], we first make the binary relaxation in constraint (3c) with box constraints as follows

$$\mathbf{x}_{m,k} \in [0,1], \forall m \in \mathcal{M}, k \in \mathcal{K}. \quad (4)$$

Realizing the characteristics of binary variables, we can easily observe that $\mathbf{x}_{m,k}^2 \leq \mathbf{x}_{m,k}, 0 \leq \mathbf{x}_{m,k} \leq 1$. The equality holds true when $\mathbf{x}_{m,k} \in \{0,1\}$. Since the binary variables and its square are in the box range, the equality only happens when they are approached 0 or 1. By exploiting those characteristics, we introduce the penalty approach in order to zero-force the subtraction between $\mathbf{x}_{m,k}$ and its square. The new EE optimization problem can be reformulated as follows

$$\begin{aligned} \max_{\mathbf{x},\mathbf{p}} \mathcal{P}_2(\mathbf{x},\mathbf{p}) \triangleq \frac{\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} \mathbf{x}_{m,k}^2 \mathcal{R}_{m,k}(\mathbf{x}^2,\mathbf{p})}{\sum_{m\in\mathcal{M}} \mathbf{p}_m + p_{non}} \\ + \Theta \sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} (\mathbf{x}_{m,k}^2 - \mathbf{x}_{m,k}), \\ \text{s.t} \quad (3b), (3d) - (3e), (4), \end{aligned} \tag{5}$$

where Θ is the positive penalty factor which downgrade the gap of the subtraction term $(\mathbf{x}_{m,k}^2 - \mathbf{x}_{m,k})$ to zero.

Even though (5) is relaxed with continuous association variables, the optimization problem is still complex with non-convex structure. Therefore, finding the optimal solution for (5) still suffer from many difficulties due to the non-concavity of the objective function and nonconvexity of the feasible sets. In the following, the alternating descent method is introduced to split the primal problem into two separated subproblems, which makes the problem easy to handle concurrently at the same iteration. In details, the SBS-UE association problem is handled while keeping the transmit power as a constant. Next, the transmit power is optimized based on the constant optimal association variables which found in the previous step. In such schemes, the increment of the objective function is guaranteed at each iteration until its convergence [15]. Since those subproblems are still in nonconvexity structures, the successive convex programming is developed to provide computationally low-complexity algorithms by solving the simple quadratic convex problem at each iteration [10,13,15].

3.1 SBS-UE Association Problem

By exploiting the alternating descent approach, we first focus on the SBS-UE association problem while ignoring the power allocation variables. Let us fix $\mathbf{p} \triangleq p^{(\kappa)}$. Denote $\boldsymbol{t}(\mathbf{p}) = \left(\sum_{m\in\mathcal{M}} \mathbf{p}_m + p_{non}\right)$. The optimization problem (5) remains as

$$\begin{aligned} \max_{\mathbf{x}} \mathcal{P}_2(\mathbf{x},p) \triangleq \sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} \mathbf{x}_{m,k}^2 \mathcal{R}_{m,k}(\mathbf{x}^2,p)/\boldsymbol{t}(p) \\ + \Theta \sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} (\mathbf{x}_{m,k}^2 - \mathbf{x}_{m,k}), \\ \text{s.t} \quad (3b), (3e), (4). \end{aligned} \tag{6}$$

By applying inequalities (22) for the UE achievable rate $(\mathbf{x}^2_{m,k}\mathcal{R}_{m,k}(\mathbf{x}^2,p))$ and (24) for the penalty term $(\mathbf{x}^2_{m,k} - \mathbf{x}_{m,k})$ in the Appendix to (6), we obtain the lower bound as

$$\begin{aligned}\mathcal{P}_2(\mathbf{x},p) &\geq \sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}}\lambda^{(\kappa)}_{m,k}(\mathbf{x},p)/\boldsymbol{t}(p) + \Theta\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}}\mu^{(\kappa)}_{m,k}(\mathbf{x})\\ &\triangleq \mathcal{P}^{(\kappa)}_2(\mathbf{x},p),\end{aligned} \tag{7}$$

where

$$\begin{aligned}\lambda^{(\kappa)}_{m,k}(\mathbf{x},p) &\triangleq \frac{(x^{(\kappa)}_{m,k})^2\log_2(1+\gamma_{m,k})}{\mathcal{K}_m((x^{(\kappa)}_{m,k})^2)}\\ &\quad+\frac{2x^{(\kappa)}_{m,k}\log_2(1+\gamma_{m,k})(\mathbf{x}_{m,k}-x^{(\kappa)}_{m,k})}{\mathcal{K}_m((x^{(\kappa)}_{m,k})^2)}\\ &\quad-\frac{(x^{(\kappa)}_{m,k})^2\log_2(1+\gamma_{m,k})}{(\mathcal{K}_m((x^{(\kappa)}_{m,k})^2))^2}\\ &\qquad(\mathcal{K}_m((\mathbf{x}_{m,k})^2)-\mathcal{K}_m((x^{(\kappa)}_{m,k})^2)),\\ \mu^{(\kappa)}_{m,k}(\mathbf{x}) &\triangleq ((x^{(\kappa)}_{m,k})^2 - x^{(\kappa)}_{m,k} + (2x^{(\kappa)}_{m,k}-1)(\mathbf{x}_{m,k}-x^{(\kappa)}_{m,k})).\end{aligned} \tag{8}$$

The positive penalty factor Θ can be found at the initial step as follows

$$\Theta = \left|(\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}}\lambda^{(0)}_{m,k}(\mathbf{x},p)/\boldsymbol{t}(p^{(0)}))\backslash(\sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}}\mu^{(0)}_{m,k})(\mathbf{x})\right|. \tag{9}$$

On the other hand, by applying inequality (23) in the Appendix for non-convex QoS constraint (3e) yields that

$$\begin{aligned}\sum_{m\in\mathcal{M}}\mathbf{x}_{m,k}\mathcal{R}_{m,k}(\mathbf{x},p) \geq \sum_{m\in\mathcal{M}}\log_2(1+\gamma_{m,k})\\ \left(\frac{2\sqrt{x^{(\kappa)}_{m,k}}\sqrt{\mathbf{x}_{m,k}}}{\mathcal{K}_m(x^{(\kappa)}_{m,k})} - \frac{x^{(\kappa)}_{m,k}}{(\mathcal{K}_m(x^{(\kappa)}_{m,k}))^2}\mathcal{K}_m(\mathbf{x}_{m,k})\right).\end{aligned} \tag{10}$$

Thus, the SBS-UE association optimization problem can be expressed as follows

$$\begin{aligned}&\max_{\mathbf{x}}\mathcal{P}^{(\kappa)}_2(\mathbf{x},p)\\ \text{s.t}\quad &(3b),(4),(10).\end{aligned} \tag{11}$$

Instead of finding the global optimum for (6), the problem can be targeted by solving lower bound maximization (11), which generates the feasible point $x^{(\kappa+1)}$

to improve the objective function in $x^{(\kappa)}$. Generally, at the initial point $x^{(0)}$, the optimization problem (11) will generate the set of sequence $x^{(\kappa)}, \kappa = 1, 2, \ldots$ such that

$$\begin{aligned}\mathcal{P}_2(x^{(\kappa+1)}, p) &\geq \mathcal{P}_2^{(\kappa)}(x^{(\kappa+1)}, p)\\ &\geq \mathcal{P}_2^{(\kappa)}(x^{(\kappa)}, p)\\ &= \mathcal{P}_2(x^{(\kappa)}, p). \end{aligned} \tag{12}$$

In particular, $x^{(\kappa-1)}$ is used as a feasible point to obtain $x^{(\kappa)}$ until the convergence.

3.2 Power Allocation Problem

In the power allocation problem, we fix $\mathbf{x} \triangleq x^{(\kappa+1)}$, which is the optimal $\mathbf{x}^\star$ found in the previous step. Thus, the power allocation problem is in the form

$$\begin{aligned}&\max_{\mathbf{p}} \mathcal{P}_2(x, \mathbf{p}) \triangleq \sum_{m\in\mathcal{M}}\sum_{k\in\mathcal{K}} x_{m,k}^2 \mathcal{R}_{m,k}(x^2, \mathbf{p})/\boldsymbol{t}(\mathbf{p}),\\ &\text{s.t} \quad (3d), (3e).\end{aligned} \tag{13}$$

By applying inequality (21) in the Appendix to (5), we obtain the lower bound for $\mathcal{R}_{m,k}(x^2, \mathbf{p})$

$$\begin{aligned}&\mathcal{R}_{m,k}(x^2, \mathbf{p}) \geq\\ &\alpha_{m,k} + \beta_{m,k}\left(1 - \frac{p_m^{(\kappa)}}{\mathbf{p}_m} + \frac{\sum_{n\in\mathcal{M}\backslash\{m\}} (p_n^{(\kappa)} - \mathbf{p}_n) g_{n,k}}{\sum_{n\in\mathcal{M}\backslash\{m\}} p_n^{(\kappa)} g_{n,k} + \sigma_m^2}\right),\\ &\triangleq \mathcal{R}_{m,k}^{(\kappa)}(x^2, \mathbf{p}),\end{aligned} \tag{14}$$

which is the concave function with

$$\begin{aligned}&0 \leq \alpha_{m,k} = \frac{W}{\mathcal{K}_m(x^2)} \log_2\left(1 + \frac{p_m^{(\kappa)} g_{m,k}}{\sum_{n\in\mathcal{M}\backslash\{m\}} p_n^{(\kappa)} g_{n,k} + \sigma_m^2}\right),\\ &0 \leq \beta_{m,k} = \frac{W}{\mathcal{K}_m(x^2)}\\ &\qquad\left(\frac{(p_m^{(\kappa)} g_{m,k})/(\sum_{n\in\mathcal{M}\backslash\{m\}} p_n^{(\kappa)} g_{n,k} + \sigma_m^2)}{1 + (p_m^{(\kappa)} g_{m,k})/(\sum_{n\in\mathcal{M}\backslash\{m\}} p_n^{(\kappa)} g_{n,k} + \sigma_m^2)}\right).\end{aligned} \tag{15}$$

Algorithm 1. Alternating descent algorithm for EE optimization algorithm

Initialization Initial any feasible point $x^{(0)}$, $p^{(0)}$. Run (18) to find a feasible point $p^{(\kappa)}$ for (5). Obtain Θ according to (9). Set $\kappa = 0$.
repeat
  Solve (11) with $\mathbf{p} = p^{(\kappa)}$ to find $x^{(\kappa+1)}$.
  Solve (16) with $\mathbf{x} = x^{(\kappa+1)}$ to find $p^{(\kappa+1)}$.
  Set $\kappa = \kappa + 1$.
until convergence

Thus, solving (13) is equal to find the feasible point $p^{(\kappa)}$ in the following problem

$$\max_{\mathbf{p}} \mathcal{P}_2^{(\kappa)}(x, \mathbf{p}) \triangleq \sum_{m\in\mathcal{M}} \sum_{k\in\mathcal{K}} x_{m,k}^2 \mathcal{R}_{m,k}^{(\kappa)}(x^2, \mathbf{p}) - \Xi(p^{(\kappa)})\mathbf{t}(\mathbf{p}), \tag{16a}$$

$$\text{s.t } (3d), \sum_{m\in\mathcal{M}} x_{m,k}\mathcal{R}_{m,k}^{(\kappa)}(x, \mathbf{p}) \geq \mathcal{R}_k^{min}, \forall k \in \mathcal{K}, \tag{16b}$$

where $\Xi(p^{(\kappa)})$ is obtained at each iteration as follows

$$\Xi(p^{(\kappa)}) = (\sum_{m\in\mathcal{M}} \sum_{k\in\mathcal{K}} x_{m,k}^2 \mathcal{R}_{m,k}(x^2, p^{(\kappa)}))\backslash(\mathbf{t}(p^{(\kappa)})). \tag{17}$$

Similar to the previous step, $p^{(\kappa)}, \kappa = 1, 2, \ldots$ is found from the initial point $p^{(0)}$ by iteratively solving (16). Thus, the increment of the objective function is guaranteed since the optimal variables $p^{(\kappa+1)}$ improve the objective function at the $(\kappa+1)$-th iteration better than the objective function in the (κ)-th iteration.

3.3 Initialization

In order to solve (5), it is necessary to find the feasible point $\mathbf{p}$ for QoS constraint (3e). Let us define the initialization problem as follows

$$\max_{\mathbf{p}} \min_{k=1,\ldots,K} \sum_{m\in\mathcal{M}} \mathcal{R}_{m,k}^{(\kappa)}(x^2, \mathbf{p}) \quad \text{s.t} \quad (3d). \tag{18}$$

We run iteratively the problem (18) until the ratio of $(\sum_{m\in\mathcal{M}} \mathcal{R}_{m,k}^{(\kappa)}(x^2, \mathbf{p}))/(\mathcal{R}_k^{min}) \geq 1, \forall k \in \mathcal{K}$. Then reset $\kappa \Rightarrow 0$. It can be observe that the minimum achievable rate among UEs in (18) is increased at each iteration until the their QoS requirements are satisfied. The feasible initial point $\mathbf{p}$ is thus provided for solving (5).

From the initial point $x^{(0)}$, $p^{(0)}$, the above procedures improve the objective function in (5). In details, the SBS-UE association problem in (6) and the power

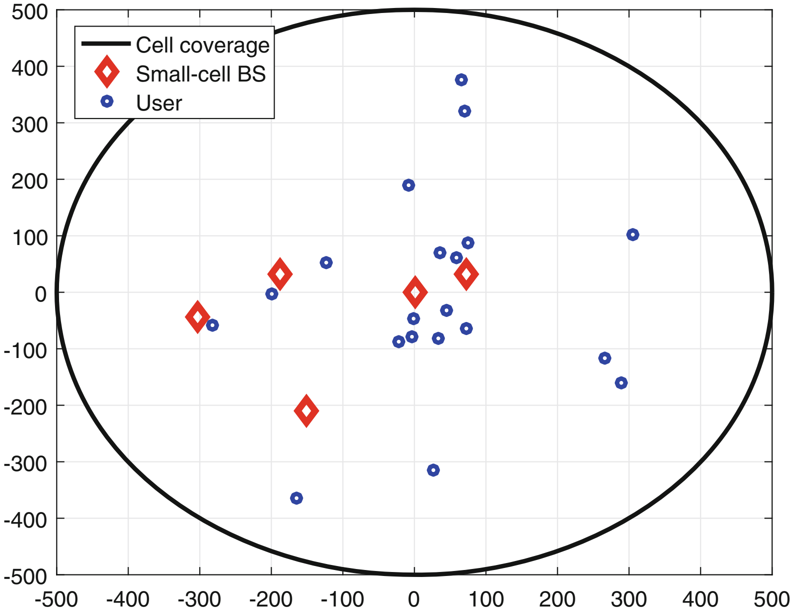

Fig. 2. The dense network scenario with $M = 5$ SBSs and $K = 20$ UEs randomly distributed in the circular cell.

allocation problem in (13) are alternatively solved to improve the problem (5), which make $(\mathbf{x}, \mathbf{p})$ converges to the optimal point at the finite iterations. The increment procedure for (5) can be expressed as

$$\begin{aligned}\mathcal{P}_2(\mathbf{x}^{(\kappa+1)}, \mathbf{p}^{(\kappa+1)}) &\geq \mathcal{P}_2^{(\kappa)}(\mathbf{x}^{(\kappa+1)}, \mathbf{p}^{(\kappa+1)}) \\ &\geq \mathcal{P}_2^{(\kappa)}(x^{(\kappa+1)}, \mathbf{p}^{(\kappa)}) = \mathcal{P}_2(\mathbf{x}^{(\kappa+1)}, \mathbf{p}^{(\kappa)}) \\ &\geq \mathcal{P}_2^{(\kappa)}(\mathbf{x}^{(\kappa+1)}, p^{(\kappa)}) \\ &\geq \mathcal{P}_2^{(\kappa)}(\mathbf{x}^{(\kappa)}, p^{(\kappa)}) = \mathcal{P}_2(\mathbf{x}^{(\kappa)}, \mathbf{p}^{(\kappa)}).\end{aligned} \tag{19}$$

Note that, the convergence is activated with a small ϵ value when the below condition is triggered

$$\left| \frac{\mathcal{P}_2(\mathbf{x}^{(\kappa+1)}, \mathbf{p}^{(\kappa+1)}) - \mathcal{P}_2(\mathbf{x}^{(\kappa)}, \mathbf{p}^{(\kappa)})}{\mathcal{P}_2(\mathbf{x}^{(\kappa)}, \mathbf{p}^{(\kappa)})} \right| \geq \epsilon. \tag{20}$$

The alternating descent method to solve EE maximization problem is summarized in Algorithm 1.

4 Numerical Results

In this section, Monte Carlo simulations are implemented to demonstrate the efficiency of our proposed algorithms. Consider the ultra-dense networks consisting of $M = 5$ SBSs and $K = 20$ UEs randomly distributed in the cell, as shown in Fig. 2. Following [20], we set $l_{m,k}^{Tx} = l_{m,k}^{Rx} = 1$, $\xi = 5$ mm, $\eta = 3$ and $d_0 = 1$ m. Without loss of generality, we assume that $\mathcal{P}_m^{max} = \mathcal{P}^{max}, \forall m \in \mathcal{M}$ and $\mathcal{R}_k^{min} = \mathcal{R}^{min}, \forall k \in \mathcal{K}$. The convergence threshold is set as $\epsilon = 1\text{e}{-4}$. The other parameters are summarized by Table 1 [9,20].

Table 1. Parameter settings

Parameter	Value
Cell radius	500 m
Bandwidth ($\mathcal{B}$)	1200 MHz
The maximum transmit power	4.7 dBm
Antenna power consumption	5.6 mW
Noise power density	−134 dBm/MHz

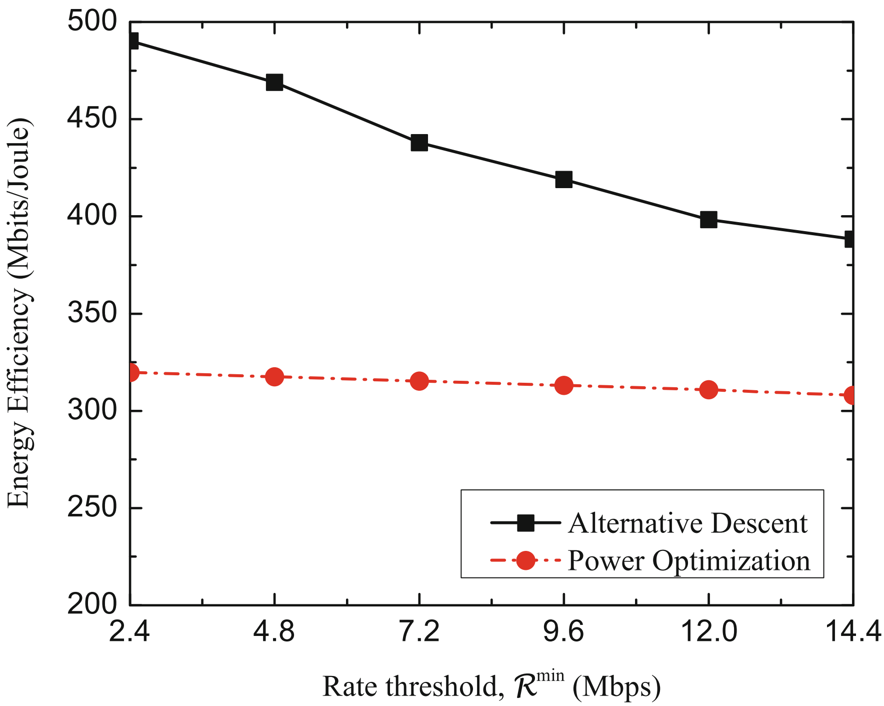

Fig. 3. The achievable EE versus $\mathcal{R}^{min}$ comparing to random SBS-UE association scenario.

In Fig. 3, we investigate the effects of UE QoS requirements on the achievable EE. We compare the achievable EE of the joint SBS-UE association and power allocation schemes, namely Alternative Descent with the random SBS-UE association scheme, namely Power Optimization. In the Power Allocation scheme, each UE selects the SBS which has the largest channel gain to associate, then the power allocation scheme is applied to optimize the transmit power in achieving EE maximization. From the plot, it can be observed that without SBS-UE association scheme, the achievable EE is strongly reduced while our proposed algorithm outperforms the Power Optimization scheme. On the other hand, we can observe from the figure that the Alternative Descent curve continuously decreases when $\mathcal{R}^{min}$ increases. This is due to the fact that when UE increases their QoS thresholds, all SBSs must increase their transmit power to meet the requirements while the total throughput is slightly scaled, which leads to the reduction on the achievable EE.

In Fig. 4, we demonstrate the computational low-complexity and convergence of our proposed algorithms. Observing from [20], solving those optimization schemes are usually based on the conventional Lagrangian and subgradient method. Therefore, their solutions are very complex and require large iterations for convergence. From the figure, it can be seen that our proposed solution is rapidly converged to the optimal performance, which requires around 12 itera-

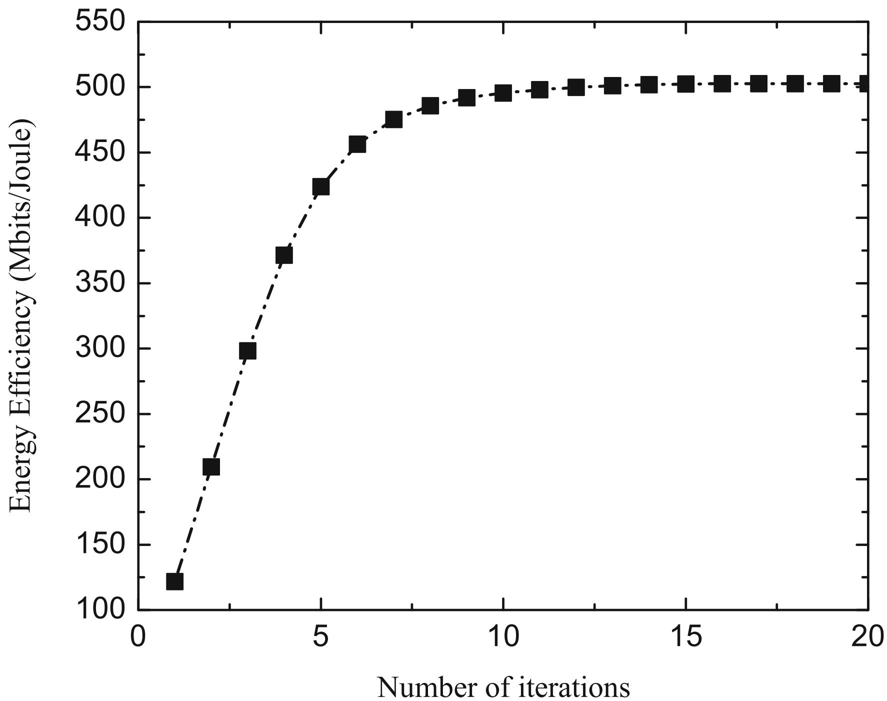

Fig. 4. Convergence of the proposed EE optimization with $r_{min} = 2.4$ Mbps.

tions. Thus, the results demonstrate the efficiency of our low-complexity solution, where the increment of the objective is guaranteed for each iteration.

5 Conclusions

In this paper, the new approaches for jointly optimizing SBS-UE association and power allocation have been proposed in the context of 60 GHz millimeter-wave ultra-dense networks. Our proposed methods have been targeted on maximizing the system EE subject to the QoS requirements of each UE. Since the SBS-UE association problem is one of the difficult classes of the mixed integer non-convex optimization problem, it is very challenging to solve together with non-convex power allocation scheme. Thanks to the help from alternating descent algorithm, the primal problem was divided into two suboptimization problems, which are handled one-by-one at each iteration. More specifically, the penalty approach has been applied to reformulate the challenging SBS-UE association problem. Finally, successive optimization methods were developed to reformulate non-convex optimization problem into low-complexity quadratic convex optimization problem with guaranteeing the increment of the objective at each iteration. The numerical results demonstrated the computational low-complexity and effectiveness of our proposed algorithms.

Appendix: Fundamental Inequalities

As the function $f(x, y) \triangleq \ln(1 + 1/xy)$ is convex in the domain $\{x > 0, y > 0\}$ [12], it follows that [16] for every $x > 0$, $y > 0$, $\bar{x} > 0$ and $\bar{y} > 0$,

$$\begin{aligned} \ln(1 + 1/xy) &= f(x, y) \\ &\geq f(\bar{x}, \bar{y}) + \langle \nabla f(\bar{x}, \bar{y}), (x, y) - (\bar{x}, \bar{y}) \rangle \\ &= \ln(1 + 1/\bar{x}\bar{y}) + \frac{1/\bar{x}\bar{y}}{1 + 1/\bar{x}\bar{y}}(2 - x/\bar{x} - y/\bar{y}). \end{aligned} \tag{21}$$

Reutilizing inequalities in [15], we observe that function x^2/t is always convex under condition of $x > 0$ and $t > 0$, which yields inequality

$$\frac{x^2}{t} \geq \frac{2\bar{x}}{\bar{t}}x - \frac{\bar{x}^2}{\bar{t}^2}t. \tag{22}$$

Then substituting $x \to \sqrt{x}$ and $\bar{x} \to \sqrt{\bar{x}}$, we obtain

$$\frac{x}{t} \geq \frac{2\sqrt{\bar{x}}}{\bar{t}}\sqrt{x} - \frac{\bar{x}}{\bar{t}^2}t. \tag{23}$$

Lastly, the inequality

$$x^2 - x \geq \bar{x}^2 - \bar{x} + (2\bar{x} - 1)(x - \bar{x}) \tag{24}$$

always hold true since $x^2 - x$ is in convex quadratic form [15].

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