Joint VBS Association and Resource Allocation for Wireless Network Virtualization-enabled Heterogeneous Integrated Networks

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ABSTRACT

In this paper, we consider a heterogeneous integrated network scenario where a number of heterogeneous radio access technologies are integrated to offer data transmission service to user equipments (UEs). We assume that wireless network virtualization is applied to the networks and the physical base stations (PBSs) of the access networks are virtualized into a number of virtual base stations (VBSs). We jointly study VBS association and resource allocation problem in the networks. To achieve joint performance optimization of all the UEs within the network, we formulate thejoint VBS association and resource allocation problem as an optimization problem which aims at achieving the maximumenergy efficiency of the networks. As the formulated optimization problem is aNP hard problem, which cannot be solved directly, we propose a heuristic algorithm, which starts from a complete matching between user pairs and VBSs, and thenfor each matching pair, the original power allocation and VBS association and resource allocation problemcan be transformed into resource allocation subproblem and VBS association subproblemequivalently. The two subproblems are solved, respectively, through applying Lagrange dual method and the Kuhn-Munkres (K-M) algorithm. Numerical results demonstrate the efficiency of the proposed algorithm.

KEYWORDS

Heterogeneous integrated network, VBS association, resource allocation, energy efficiency

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1 INTRODUCTION

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achieved effective coordination and integration, resulting in heterogeneous integrated networks (HetNets). In addition, the exploding popularity of smart wireless devices and the dramatic increase in the amount of data traffic have pose great challenges on the transmission performance the radio access networks (RANs). To enhance the transmission performance of the RANs and to improve the utilization of network resources, the concept of wireless network virtualization (WNV) has been proposed, which is considered as an emerging architectural choice to support concurrent heterogeneous services with various quality of service (QoS) requirements [1]. By applying WNV technology in HetNets, physical network architectures of the network can be mapped into virtual architectures which are allowed to share the network resources of physical network. Compared to traditional networking paradigms, the network resource utilization can be improved and network resources can be managed flexibly by constructing the optimal mapping and virtualization schemes [2, 3].

Despite the potential advantages of WNV to improve wireless resource utilization, it brings many new challenges [3]. One such research challenge is how to efficiently allocate the wireless resources of physical networks to the users of multiple virtual networks. Many previous works have been conducted on the resource allocation of wireless networks enabling WNV. The authors in [4] introduce wireless virtualization into small cell networks and propose a virtual resource allocation problem in virtualized small cell networks with full-duplex self-backhaul in the downlink transmission and formulate the optimization problem to maximize the total utility of mobile virtual network operators (MVNOs). In [5], the authors propose a virtualization framework for LTE systems, where the physical resources of the eNodeB are allocated to the service providers by a central entity called hypervisor.

Reference [6] solves resource allocation problems in wireless networks based on game theoretic approach. In particular, the authors apply stochastic game framework to model the interactions between network operator (NO) and service providers (SPs), where the NO determines the conjectural prices of network resources and SPs dynamically bid the resources on behalf of their users. The authors in [7] consider resource allocation in a multi-cell virtualized wireless networks and propose a joint base station (BS) assignment, subcarrier, and power allocation algorithm which aim at maximizing the network sum rate. In [8], the authors consider two-way relay networks and study the training-based channel estimation schemes. They derive the maximum-likelihood (ML)-based estimator for deterministic channel and a new type of estimator that aims at maximizing the effective receive signal-to-noise ratio (SNR) for stochastic channel model.

In previous research works [4–8], to maximize the network throughput or the formulated utility function, the maximum transmit power should be applied in general. However, this may result in large power consumption and low energy efficiency, which are highly undesired. To stress the tradeoff between user transmission performance and power consumption, the energy consumption and the energy efficiency of wireless networks are considered in designing resource allocation schemes.

In the works of [9 -11], the authors mainly focus on the energy efficiency performance matric which is of particular importance in future cellular systems. The authors in [9] design an iterative algorithm to maximize system energy efficiency in device-to-device (D2D) communications. In [10], the authors consider an energy efficiency maximization scheme of resource assignment and power allocation and design a low-complexity and sub-optimal algorithm. The authors in [11] transform the energy efficient resource allocation problem in wireless multicell OFDMA networks into a proportional fairness optimization problem.

While energy efficiency optimization has been considered in [9–11], user association and resource allocation issues have not been studied extensively. In [12], the authors consider the joint optimization of BS association and power allocation in a wireless downlink HetNet under the proportional fairness criterion and propose a utility function maximization based BS association and power allocation strategy. However, energy efficiency failed to be stressed in their work. In this paper, we consider a WNV-enabled HetNet where physical BSs (PBSs) are virtualized into virtual BSs (VBSs) and study joint VBS association and resource allocation problem. The rest of paper is organized as follows. The system model is described in Section 2. The proposed energy efficient resource allocation problem is formulated in Section 3. In Section 4, we describe the solution to the formulated optimization problem. Simulation results are discussed in Section 5. Finally, we conclude this study in Section 6.

2 SYSTEM MODEL

In this work, we consider a HetNet framework consisting of multiple heterogeneous RANs and a number of user equipments (UEs). Applying WNV technology, the PBSs in the networks are virtualized into multiple VBSs, which share the spectrum resource of the corresponding PBSs. We assume that orthogonal spectrum sharing scheme is applied for various PBSs in the network, hence no inter-cell interference exists.

We denote the number of PBSs as M, the number of VBSs belonging to the ith PBS as N_i and the number of UEs as K. We assume UEs located within the geographic area of the network may access the VBS of one PBS for information interaction. For convenience, we further assume that each UE can only select one VBS and each VBS can only serve one UE at certain time-frequency resource block. In this paper, we assume that the bandwidth resource of the PBSs is given constants and jointly study VBS association and resource allocation problem, in particular, we stress the bandwidth and power allocation problem of the UEs. Fig. 1 shows the system model considered in this paper.

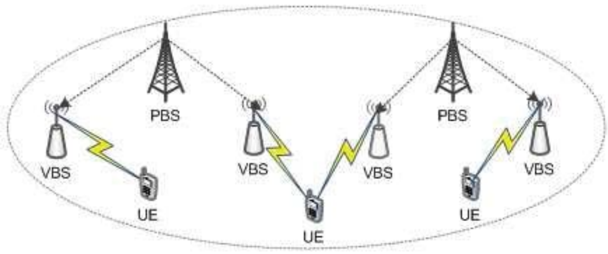

Figure 1: System Model

3 PROPOSED VBS ASSOCIATION AND RESOURCE ALLOCATION PROBLEM FORMULATION

In this section, we design the optimal joint VBS association and resource allocation scheme for the UEs in the HetNet. In particular, to stress the importance of the transmission rate and power consumption of users, and to achieve the tradeoff between the two metrics, the energy efficiency of all the UEs is examined and optimized in terms of the VBS association, bandwidth and transmit power allocation strategy.

3.1 Optimization Objective Function

Let η denote the energy efficiency of the UEs, we obtain

$$\eta = \sum_{i=1}^{M} \eta_i \tag{1}$$

where η_i denotes the energy efficiency of the UEs accessing the ith PBS, which can be expressed as

$$\eta_i = \sum_{j=1}^{N_i} \sum_{k=1}^{K} x_{ijk} \eta_{ijk} \tag{2}$$

where $x_{ijk} \in \{0, 1\}$ denotes the VBS association variable of the kth UE when accessing the jth VBS belonging to the ith PBS, we set $x_{ijk} = 1$ if the kth user accessing the jth VBS of the ith PBS; otherwise, $x_{ijk} = 0$, η_{ijk} denotes the energy efficiency of the kth UE when accessing the jth VBS of the ith PBS. η_{ijk} can be expressed as

$$\eta_{ijk} = \frac{R_{ijk}}{P_{ijk} + P_{\text{cir}}} \tag{3}$$

where R_{ijk} and P_{ijk} denote respectively the achievable data rate and the transmit power of the kth UE when accessing the jth VBS of the ith PBS, P_{cir} denotes the circuit consumption power of the UEs. We assume that the circuit consumption power of the UEs is a constant in this work. R_{ijk} in (3) can be expressed as

$$R_{ijk} = \alpha_{ijk} B_i \log\left(1 + \frac{P_{ijk} h_{ik}}{\sigma^2}\right) \tag{4}$$

where α_{ijk} denotes the fraction of the bandwidth allocated to the jth VBS of the ith PBS when accessing the kth UE, B_i denotes the available bandwidth of the ith PBS, h_{ik} denotes the channel gain of the transmission link from the kth UE to the ith PBS, and σ^2 denotes the power of the additive white Gaussian noise (AWGN) of the link from the kth UE to the ith PBS. Without loss of generality, the power of the AWGN for all the links is assumed to be a constant in this work.

3.2 Optimization Constraints

In this subsection, we describe the optimization constraints which should be satisfied when designing the optimal VBS association and resource allocation scheme.

3.2.1 Data Rate Constraint. UEs with various types of services may pose different QoS requirements on the accessing VBSs. In this paper, we assume that UEs may have different data rate requirements, more specifically, each UE has a minimum data rate requirement. The data rate of the kth UE can be calculated as

$$R_k = \sum_{i=1}^{M} \sum_{j=1}^{N_i} x_{ijk} R_{ijk}. \tag{5}$$

Denoting $R_k^{\min}$ as the minimum data rate requirement of the kth UE, we can obtain the data rate constraint:

$$R_k \geq R_k^{\min}. \tag{6}$$

3.2.2 Maximum Transmit Power Constraint. The transmit power of the kth UE can be calculated as:

$$P_k = \sum_{i=1}^{M} \sum_{j=1}^{N_i} x_{ijk} P_{ijk}. \tag{7}$$

Let $P_k^{\max}$ denote the maximum allowable transmit power of the kth UE, the transmit power of the UE should be less than $P_k^{\max}$, hence the maximum power constraint can be expressed as

$$P_k \leq P_k^{\max}. \tag{8}$$

3.2.3 VBS Association Variable Constraint. We assume that UEs can at most access one VBS and vice versa, hence the VBS association constraint can be expressed as

$$\sum_{i=1}^{M} \sum_{j=1}^{N_i} x_{ijk} \leq 1, \tag{9}$$

$$\sum_{k=1}^{K} x_{ijk} \leq 1. \tag{10}$$

3.2.4 Bandwidth Allocation Constraint. As the VBSs belonging to one PBS share the bandwidth resource of the PBS, we obtain

$$\sum_{j=1}^{N_i} \sum_{k=1}^{K} \alpha_{ijk} \leq 1, \tag{11}$$

$$0 \leq \alpha_{ijk} \leq 1. \tag{12}$$

3.3 Optimization Problem Formulation

Based on the optimization objective and constraints, the problem of VBS association and resource allocation in the HetNet can be formulated as the following optimization problem

$$\begin{aligned} \max_{x_{ijk}, \alpha_{ijk}, P_{ijk}} \quad & \eta \\ \text{s.t.} \quad & \text{C1}: R_k \geq R_k^{\min} \\ & \text{C2}: P_k \leq P_k^{\max} \\ & \text{C3}: \sum_{i=1}^{M} \sum_{j=1}^{N_i} x_{ijk} \leq 1 \\ & \text{C4}: \sum_{k=1}^{K} x_{ijk} \leq 1 \\ & \text{C5}: 0 \leq \alpha_{ijk_1} \leq 1 \\ & \text{C6}: \sum_{j=1}^{N_i} \sum_{k=1}^{K} \alpha_{ijk} \leq 1 \end{aligned} \tag{13}$$

4 SOLUTION TO THE OPTIMIZATION PROBLEM

The optimization problem formulated in (13) is a non-convex nonlinear fractional program [14] which cannot be solved conveniently using traditional optimization tools. In this section, we consider a relatively simple case, that is each PBS is virtualized into two VBSs, and transform the original optimization problem into two sub-problems, i.e., bandwidth and power allocation sub-problem and VBS association sub-problem.

4.1 Bandwidth and Power Allocation Subproblem

We assume that the ith PBS is virtualized into two VBSs, i.e., the j_1th and the j_2th VBS and the k_1th UE accesses the j_1th VBS and the k_2th UE accesses the j_2th VBS of the ith PBS, thus we obtain $x_{ij_1k_1} = 1$ and $x_{ij_2k_2} = 1$. As the two VBSs share the bandwidth resource of the ith PBS, we obtain $\alpha_{ij_2k_1} = 1 - \alpha_{ij_1k_2}$, we can then formulate the bandwidth and power allocation sub-problem as follows

$$\max_{\alpha_{ij_1k_1}, P_{ij_1k_1}, P_{ij_2k_2}} \eta_{ij_1k_1} + \eta_{ij_2k_2} \quad (14)$$
$$\begin{aligned} \text{s.t.} \quad & \text{C1}: R_{k_1} \geq R_{k_1}^{\min} \\ & \text{C2}: R_{k_2} \geq R_{k_2}^{\min} \\ & \text{C3}: P_{k_1} \leq P_{k_1}^{\max} \\ & \text{C4}: P_{k_2} \leq P_{k_2}^{\max} \\ & \text{C5}: 0 \leq \alpha_{ij_1k_1} \leq 1 \end{aligned}$$

The fractional objective function in (14) is a non-convex nonlinear fractional program, which is very difficult to be solved using conventional optimization methods. Therefore, we transformed it into a convex problem and then solved by the usage of Dinkelbach iterative algorithm [14].

4.1.1 Dinkelbach iterative algorithm-based Resource Allocation Algorithm. In (14), the optimization variable $\alpha_{ij_1k_1}$ is coupled with $P_{ij_1k_1}$ and $P_{ij_2k_2}$, thus it is difficult to separate and solve them individually. Notice that α_{ijk_1} varies within a relatively small region, i.e., $1 \leq \alpha_{ij_1k_1} \leq 1$, for simplicity, we can obtain the optimal value of $\alpha_{i_1k_1}$ numerically, for instance, by exhaustive search, then for each fixed value of $\alpha_{ij_1k_1}$, we further solve $P_{ij_1k_1}$ and $P_{ij_2k_2}$.

To obtain the optimal solution of $P_{ij_1k_1}$ and $P_{ij_2k_2}$, we introduce variable q_1 and q_2, which are defined as

$$q_1 = \frac{\alpha_{ij_1k_1} B_i \log\left(1 + \frac{P_{ij_1k_1} h_{ik_1}}{\sigma^2}\right)}{P_{ij_1k_1} + P_{\text{cir}}}, \quad (15)$$

$$q_2 = \frac{(1-\alpha_{ij_1k_1}) B_i \log\left(1 + \frac{P_{ij_2k_2} h_{ik_2}}{\sigma^2}\right)}{P_{ij_2k_2} + P_{\text{cir}}}. \quad (16)$$

We can prove that the maximum energy efficiency is obtained when the following condition holds [14].

$$\begin{aligned} \max_{P_{ij_1k_1}, P_{ij_2k_2}} & \alpha_{ij_1k_1} B_i \log\left(1 + \frac{P_{ij_1k_1} h_{ik_1}}{\sigma^2}\right) - q_1 \left(P_{i_1k_1} + P_{\text{cir}}\right) \\ & + (1-\alpha_{ij_1k_1}) B_i \log\left(1 + \frac{P_{ij_2k_2} h_{ik_2}}{\sigma^2}\right) - q_2 \left(P_{i_2k_2} + P_{\text{cir}}\right) \\ & = 0 \end{aligned} \quad (17)$$

Hence, solving the optimization formulated in (14) is equivalent to solving the following optimization problem

$$\begin{aligned} \max_{q_1, q_2, P_{ij_1k_1}, P_{ij_2k_2}} & \alpha_{ij_1k_1} B_i \log\left(1 + \frac{P_{ij_1k_1} h_{ik_1}}{\sigma^2}\right) - q_1 \left(P_{ij_1k_1} + P_{\text{cir}}\right) \\ & + (1-\alpha_{ij_1k_1}) B_i \log\left(1 + \frac{P_{ij_2k_2} h_{ik_2}}{\sigma^2}\right) \\ & - q_2 \left(P_{ij_2k_2} + P_{\text{cir}}\right) \quad (18) \\ \text{s.t.} \quad & \text{C1}: R_{k_1} \geq R_{k_1}^{\min} \\ & \text{C2}: R_{k_2} \geq R_{k_2}^{\min} \\ & \text{C3}: P_{k_1} \leq P_{k_1}^{\max} \\ & \text{C4}: P_{k_2} \leq P_{k_2}^{\max} \\ & \text{C5}: 0 \leq \alpha_{ijk_1} \leq 1. \end{aligned}$$

In order to obtain the optimal energy efficiency and the power allocation strategy of (18), we apply Dinkelbach iterative algorithm [14]. The proposed algorithm is summarized as:

Algorithm 1 Dinkelbach iterative algorithm-based Resource Allocation Algorithm

(1) Initialize the maximum number of iterations $L_{\max}$ and the maximum tolerance δ
(2) Set $q_1 = 0, q_2 = 0$ and the iteration index $l = 0$
(3) Repeat main loop
(4) For given $q_1, q_2, \alpha_{ij_1k_1}$, solve for $P'_{ij_1k_1}, P'_{ij_2k_2}$
(5) if $R_{ij_1k_1} - q_1(P'_{ij_1k_1} + P_{\text{cir}}) + R_{ij_2k_2} - q_2(P'_{ij_2k_2} + P_{\text{cir}}) \leq \delta$ then
(6) Convergence = true
(7) return $\{P^*_{ij_1k_1}, P^*_{ij_2k_2}\} = \{P'_{ij_1k_1}, P'_{ij_2k_2}\}$ and
(8) $q_1^* = \frac{R_{ij_1k_1}}{P^*_{ij_1k_1} + P_{\text{cir}}}$, $q_2^* = \frac{R_{ij_2k_2}}{P^*_{ij_2k_2} + P_{\text{cir}}}$
(9) else
(10) Set $q_1 = \frac{R_{ij_1k_1}}{P'_{ij_1k_1} + P_{\text{cir}}}$, $q_2 = \frac{R_{ij_2k_2}}{P'_{ij_2k_2} + P_{\text{cir}}}$ and $l = l + 1$
(11) Convergence = false
(12) end if
(13) until convergence = true or $l = L_{\max}$

4.1.2 Lagrange Method for Solving Locally Optimal Power Allocation Strategy. For given q_1 and q_2, we use the Lagrange approach to solve the optimization problem in (18). Upon rearranging terms, the Lagrange function can be expressed as

$$\begin{aligned} & L\left(P_{ij_1k_1}, P_{ij_2k_2}, \beta_1, \beta_2, \lambda_1, \lambda_2\right) = R_{ij_1k_1} - q_1\left(P_{ij_1k_1} + P_{\text{cir}}\right) \\ & + R_{ij_2k_2} - q_2\left(P_{ij_2k_2} + P_{\text{cir}}\right) + \beta_1\left(R_{k_1} - R_{k_1}^{\min}\right) \\ & + \beta_2\left(R_{k_2} - R_{k_2}^{\min}\right) + \lambda_1\left(P_{k_1}^{\max} - P_{k_1}\right) + \lambda_2\left(P_{k_2}^{\max} - P_{k_2}\right) \end{aligned} \quad (19)$$

where $\beta_1, \beta_2, \lambda_1, \lambda_2 \geq 0$ are Lagrange multipliers. The Lagrange dual problem of (17) can be formulated as follows

$$\min_{\beta_1, \beta_2, \lambda_1, \lambda_2} \max_{P_{ij_1k_1}, P_{ij_2k_2}} L\left(P_{ij_1k_1}, P_{ij_2k_2}, \beta_1, \beta_2, \lambda_1, \lambda_2\right) \quad (20)$$

s.t. $\beta_1, \beta_2, \lambda_1, \lambda_2 \geq 0$

The above dual problem can be solved by iteratively decomposing it into two subproblems, i.e., optimizing the transmit power for a fixed set of Lagrange multipliers, and updating the Lagrange multipliers iteratively. For a given set of Lagrange multipliers β_1, β_2, λ_1, λ_2, using standard optimization techniques, we can find the locally optimal power allocation strategy through calculating the derivative of $L\left(P_{ij_1k_1}, P_{ij_2k_2}, \beta_1, \beta_2, \lambda_1, \lambda_2\right)$ over $P_{ij_1k_1}, P_{ij_2k_2}$ and setting to 0. The Karush-Kuhn-Tucker (KKT) specifies:

$$\frac{\partial L\left(P_{ij_1k_1}, P_{ij_2k_2}, \beta_1, \beta_2, \lambda_1, \lambda_2\right)}{\partial P_{ij_1k_1}} = 0 \quad (21)$$

$$\frac{\partial L\left(P_{ij_1k_1}, P_{ij_2k_2}, \beta_1, \beta_2, \lambda_1, \lambda_2\right)}{\partial P_{ij_2k_2}} = 0 \tag{22}$$

Therefore if $\beta_1, \beta_2, \lambda_1$ and λ_2 are given, then we can obtain the optimal P_{ijk_1} and P_{ijk_2} as follows:

$$P^*_{ij_1k_1} = \left[\frac{\left(\alpha_{ij_1k_1} + \beta_1\right) B_i}{ln2.(q_1 + \lambda_1)} - \frac{\sigma^2}{h_{ik_1}}\right]^+ \tag{23}$$

$$P^*_{ij_2k_2} = \left[\frac{(1 - \alpha_{ij_1k_1} + \beta_2) B_i}{ln2.(\lambda_2 + (1 - \alpha_{ij_1k_1}) q_2)} - \frac{\sigma^2}{h_{ik_2}}\right]^+ \tag{24}$$

where $[z]^+ = \max\{0, z\}$. For a differentiable dual function, a subgradient based method can be applied to calculate the optimum values for $\beta_1, \beta_2, \lambda_1$ and λ_2. The subgradient method is to design a step update $\beta_1, \beta_2, \lambda_1$ and λ_2 in the subgradient direction; the update can be performed as follows

$$\beta_1^{(t+1)} = \left[\beta_1^{(t)} - a_1(R_{k_1} - R_{k_1}^{\min})\right]^+ \tag{25}$$

$$\beta_2^{(t+1)} = \left[\beta_2^{(t)} - a_2(R_{k_2} - R_{k_2}^{\min})\right]^+ \tag{26}$$

$$\lambda_1^{(t+1)} = \left[\lambda_1^{(t)} - a_3(P_{k_1}^{\max} - P_{k_1})\right]^+ \tag{27}$$

$$\lambda_2^{(t+1)} = \left[\lambda_2^{(t)} - a_4(P_{k_2}^{\max} - P_{k_2})\right]^+ \tag{28}$$

where t is the iteration index and $a_1,\ a_2,\ a_3,\ a_4$ are small positive step sizes. The process of computing the optimal power allocation strategy $P^*_{ij_1k_1}$ and $P^*_{ij_2k_2}$ and updating $\beta_1, \beta_2, \lambda_1$ and λ_2 is repeated until convergence, indicating that the dual optimal point has been reached.

4.2 Optimal VBS Association Subproblem

Through assuming $x_{ij_1k_1} = 1$, $x_{ij_2k_2} = 1$, we can obtain the locally optimal power allocation strategy, denoted as $P^*_{ij_1k_1}$ and $P^*_{ij_2k_2}$. Substituting the optimal solutions in (1) and (2), we obtain

$$\eta = \sum_{i=1}^{M} \sum_{k_1=1}^{K} \sum_{k_2=1, k_2 \neq k_1}^{K} \left(x_{ij_1k_1}\eta^*_{ij_1k_1} + x_{ij_2k_2}\eta^*_{ij_2k_2}\right) \tag{29}$$

where $\eta^*_{ij_1k_1}$ and $\eta^*_{ij_2k_2}$ can be expressed respectively as

$$\eta^*_{ij_1k_1} = \frac{\alpha_{ij_1k_1} B_i \log\left(1 + \frac{P^*_{ij_1k_1} h_{ik_1}}{\sigma^2}\right)}{P^*_{ij_1k_1}}, \tag{30}$$

$$\eta^*_{i_2k_2} = \frac{\alpha_{ijk} B_i \log\left(1 + \frac{P^*_{i,j,k_2} h_{i,k}}{\sigma^2}\right)}{P^*_{i,j,k_2}}. \tag{31}$$

For given $P^*_{ij_1k_1}$ and $P^*_{ij_2k_2}$, $\eta^*_{ij_1k_1}$ and $\eta^*_{ij_2k_2}$ are constants. Therefore, the problem of maximizing (29) is equivalently simplified as selecting the optimal $x_{ij_1k_1}$ and $x_{ij_2k_2}$ subject to VBS association constraints, which can be expressed as the following optimal VBS association subproblem

$$\max_{x_{ij_1k_1}, x_{ij_2k_2}} \sum_{i=1}^{M} \sum_{k_1=1}^{K} \sum_{\substack{k_2=1,\\ k_2 \neq k_1}}^{K} \left(x_{ij_1k_1}\eta^*_{ij_1k_1} + x_{ij_2k_2}\eta^*_{ij_2k_2}\right) \tag{32}$$

$$\text{s.t.} \quad \text{C1}: \sum_{i=1}^{M} x_{ij_1k_1} \leq 1$$

$$\text{C2}: \sum_{i=1}^{M} x_{ij_2k_2} \leq 1$$

$$\text{C3}: \sum_{k_1=1}^{K} \sum_{k_2=1, k_2 \neq k_1}^{K} x_{ij_1k_1} + x_{ij_2k_2} \leq 2$$

The optimization model formulated in (32) is a nonlinear integer optimization problem, which is in general very difficult to solve. However, under the assumption that each PBS is virtualized into two VBSs and each VBS can only access one user, we can first partition K users into $\frac{K}{2}$ groups and design the optimal VBS association strategy for each group. It can be observed that given the constraints on VBS association and user grouping strategy, the optimization problem can be described by a bipartite graph and the problem of optimal group-VBS association can be regarded as an optimal matching problem in the bipartite graph, which can then be solved based on the typical algorithm such as Kuhn-Munkres (K-M) algorithm to obtain the optimal energy efficiency. For various user grouping strategies, we repeat above procedure to calculate the locally optimal VBS association strategy and obtain the corresponding optimal energy efficiency. Finally, we compare the obtained energy efficiency corresponding to different user grouping results and select the grouping and VBS association strategy corresponding to the maximum energy efficiency.

5 NUMERICAL RESULTS

In this section, the performance of the proposed algorithm is evaluated via numerical simulations based on Matlab. In the simulation, we consider a virtualized HetNet scenario consisting VBS and UEs, respectively. The numbers of PBSs and UEs are respectively chosen to be 2 and 4. We assume that all PBSs and UEs are located in a rectangular region with the size being 100m× 100m. We consider that the position of all BSs is fixed whiles we randomize that of the UEs. We assume the system bandwidth of two PBSs is respectively set to be 1MHz and 2MHz, and the power of noise is $\sigma^2 = -136dBm$. The minimum data rate requirement of UEs is set as 1Mbits/s, 1.5Mbits/s, 1.5bits/s and 2Mbits/s. We average the simulation results over 2000 independent adaptation processes where different realizations of the positions of the UEs is performed in each adaptation process.

Figure 2 shows the energy efficiency versus the number of iterations obtained from the proposed algorithm. The maximum transmit power, i.e., $P^{\max}$ is chosen as 1W in plotting the figure. From the figure, it can be observed that the energy efficiency monotonically increases and converges within a small number of iteration.

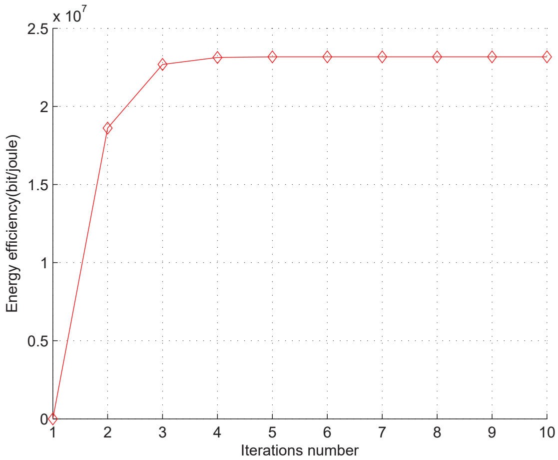

Figure 2: Energy efficiency versus the number of iteration

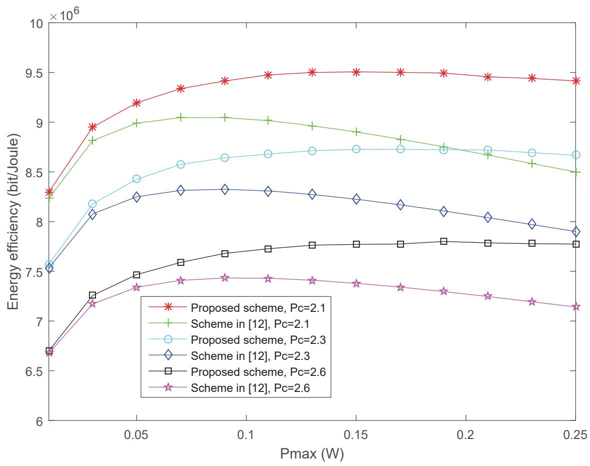

Figure 3: Energy efficiency versus $P_{\max}$ (different circuit power)

Figure 3 shows the energy efficiency versus the maximum transmit power of UEs, i.e., $P_{\max}$ for different circuit power consumption. For comparison, for a given $P_{\max}$, we plot the energy efficiency obtained from our proposed algorithm and the algorithm proposed in [12].From the figure, it can be seen that for small $P_{\max}$, the energy efficiency increases with the increase of $P_{\max}$ for both algorithms, indicating that a higher maximum power threshold is desired for achieving the maximum energy efficiency. However, as $P_{\max}$ increases, the energy efficiency obtained from our proposed algorithm becomes a constant which no longer varies with the increase of

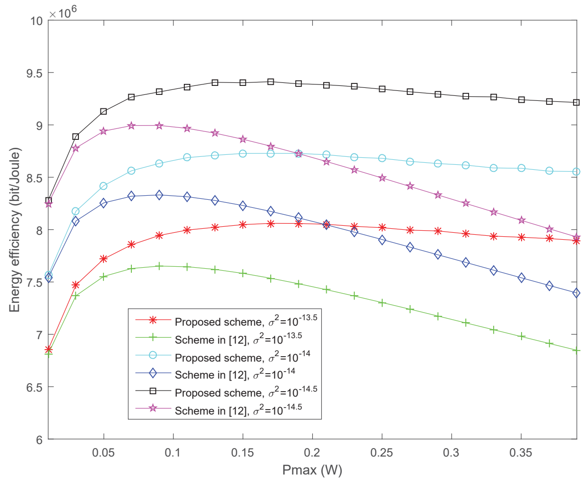

Figure 4: Energy efficiency versus $P_{\max}$ (different noise power)

$P_{\max}$. However, the energy efficiency obtained from the algorithm proposed in [12] begins to decrease after reaching the maximum value. Comparing the energy efficiency obtained for different circuit power consumption, we can see that the energy efficiency decreases with the increase of circuit power.

In Figure 4, we examine the impact of link characteristics on the energy efficiency of the UEs. Different noise power is considered in examining the performance. From the figure, we can see that as σ^2 increases, the energy efficiency decreases. This is because larger noise power results in worse transmission performance of the UEs and lower energy efficiency in turn. Comparing the results obtained from the proposed scheme and the scheme proposed in [12], it can be seen that our proposed scheme outperforms previously proposed scheme.

6 CONCLUSION

In this paper, we jointly study VBS association and power allocation problem of UEs in a WNV-enabled HetNet comprised of multiple PBSs and a number of UEs. To achieve energy efficient data transmission, the problem of joint VBS association and resource allocation is formulated as an energy efficiency maximization problem. We equivalently transform the optimization problem into two subproblems, i.e., resource allocation subproblem and VBS association subproblem, and apply iterative method and the K-M algorithm to solve the two subproblems respectively, the optimal VBS association and resource allocation strategies are obtained. Numerical results demonstrate that the proposed algorithm offers higher energy efficiency compared with previously proposed algorithm.

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REFERENCES

[1] X. Wang, P. Krishnamurthy, and D. Tipper, “Wireless network virtualization,” in *2013 International Conference on Computing, Networking and Communications (ICNC)*, pp. 818–822, 2013.

[2] C. Liang, F. R. Yu, and X. Zhang, “Information-centric network function virtualization over 5G mobile wireless networks,” *IEEE Network*, vol. 29, no. 3, pp. 68–74, May 2015.

[3] C. Liang and F. R. Yu, “Wireless network virtualization for next generation mobile cellular networks,” *IEEE Commu Maga*, vol. 22, no. 1, pp. 61-69, Mar. 2015.

[4] L. Chen, F. R. Yu, H. Ji, G. Liu, and V.C.M. Leung, “Distributed virtual resource allocation in small cell networks with full duplex self-backhauls and virtualization,” *IEEE Trans. Veh. Tech.*, vol. 65, no. 7, pp. 5410-5423, July 2016.

[5] M. Kamel, L. B. Le, and A. Girard, “LTE multi-cell dynamic resource allocation for wireless network virtualization,” in *Proc. IEEE WCNC'2015*, New Orleans, LA, Mar. 2015.

[6] F. Fu and U. C. Kozat, “Stochastic game for wireless network virtualization,” *IEEE/ACM Trans. Networking*, vol. 21, no. 1, pp. 84-97, Apr. 2013.

[7] S. Parsaeefard, R. Dawadi, M. Derakhshani, and T. Le-Ngoc, “Joint user-association and resource-allocation in virtualized wireless networks,” *IEEE Access*, pp. 2738-2750, 2016.

[8] F. Gao, R. Zhang, and Y.-C. Liang, “Optimal channel estimation and training design for two-way relay networks,” *IEEE Trans. Commun.*, vol. 57, no. 10, pp. 3024-3033, Oct. 2009.

[9] Y. Jiang, Q. Liu, F. Zheng, X. Gao and X. You, “Energy efficient joint resource allocation and power control for D2D Communications,” *IEEE Trans. Veh. Technol.*, no. 99, Aug. 2015.

[10] D. Ng, E. Lo, and R. Schober, “Energy-efficient resource allocation in OFDMA systems with large numbers of base station antennas,” *IEEE Trans. Wireless Commun.*, vol. 11, no. 9, pp. 3292 - 3304, Sep. 2012.

[11] S. Buy and F. Richard Yu, “Distributed energy-efficient resource allocation with fairness in wireless multicell OFDMA networks,” in *GLOBECOM, 2014*, Austin, TX, Dec. 2014, pp. 4708 - 4713.

[12] K. Shen and W. Yu, “Distributed pricing-based user association for downlink heterogeneous cellular networks,” *IEEE Journal on Selected Areas in Commun*, vol. 32, no. 6, pp. 1100-1113, Jun. 2014.

[13] S. Boyd and L. Vandenberghe, Convex Optimization. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[14] W. Dinkelbach, “On nonlinear fractional programming,” In *Management Science*, vol. 13, pp. 492-498 (1967). Available: http://www.jstor.org/stable/2627691.