Distributed Resource Allocation for Virtualized Small Cell Networks with Full Duplex Self-backhauls

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Abstract—Wireless network virtualization has attracted great attentions from both academia and industry. Another emerging technology for next generation wireless networks is in-band full duplex (FD) communications. Due to its promising performance, FD communication has been considered as an effective way to achieve self-backhauls for small cells. In this paper, we introduce wireless virtualization into small cell networks, and propose a virtualized small cell network architecture with FD self-backhauls. We formulate the virtual resource allocation problem in virtualized small cell networks with FD self-backhauls as an optimization problem. Since the formulated problem is a mixed combinatorial and non-convex optimization problem, its computational complexity is high. Moreover, the centralized scheme may suffer from signaling overhead, outdated dynamics information, and scalability issues. To solve it efficiently, we divide the original problem into two subproblems. For the first subproblem, we transfer it to a convex optimization problem, and then solve it by an efficient alternating direction method of multipliers (ADMM)-based distributed algorithm. The second subproblem is a convex problem, which can be solved by each infrastructure provider. Extensive simulations are conducted with different system configurations to show the effectiveness of the proposed scheme.

Index Terms—Virtualization networks, small cell networks, self-backhauls, in-band full duplex communications

I. INTRODUCTION

With the tremendous growth in wireless traffic and service, it is inevitable to extend virtualization to wireless networks [1]. In wireless virtualization, the wireless network infrastructure owned by an infrastructure provider (InP) can be decoupled from the services that it provides. At the same time, mobile virtual network operators (MVNOs) provide services to users. Since the physical resources are abstracted and sliced into virtual resources, it is possible that different MVNOs coexist on the same InP to share the infrastructure and radio spectrum resources, which enables the reducing of capital expenses (CapEx) and operation expenses (OpEx) [2].

Although some excellent researches have been done for wireless virtualization, most existing works do not consider small cell networks with self-backhauls. Recently, small cell networks have been regarded as one of the key components of next generation cellular networks to improve spectrum efficiency and energy efficiency [3]–[5]. Traditionally, there are two kinds of backhauls in small cell networks: wired backhaul (e.g., optical or DSL) and wireless backhaul (e.g., microwave or millimeter waves). Since these traditional backhauls are very expensive for infrastructure deployments, self-backhauled small cells have attracted great attentions from both academia and industry. Wireless self-backhauling can improve reachability and coverage by easing connectivity between nodes. In [6], a self-backhauling scheme was proposed, in which the self-backhaul link uses the same spectrum with the small cell downlink, but on different time slots.

Another emerging technology for next generation wireless networks is in-band full duplex (FD) communications [7]. With the recent advances of self-interference cancellation techniques, it is possible for radios to transmit and receive simultaneously in the same frequency band. Due to its promising performance, FD communication has been considered as an effective way to achieve self-backhauls for small cells.

Despite the potential vision of small cell networks with FD self-backhauls and virtualization, many research challenges remain to be addressed. One of the main research challenges is resource allocation, which plays an important role in traditional cellular networks [8], [9]. To the best of our knowledge, the problem of virtual resource allocation in small cell networks with FD self-backhauls and virtualization has not been studied in previous works.

In this paper, we first introduce wireless virtualization into small cell networks and propose a virtualized small cell networks architecture. Furthermore, we formulate the virtual resource allocation problem in virtualized small cell networks with FD self-backhauls as an optimization problem to maximize the total utility of all MVNOs. To solve the optimization problem effectively, we divide the original problem into two subproblems. By introducing an efficient alternating direction method of multipliers (ADMM)-based distributed algorithm, the first subproblem can be solved without exchange of channel state information with fast convergence rate. The second subproblem is a convex problem, which can be solved by each InP. What’s more, extensive simulations are conducted with different system configurations to verify the effectiveness of the proposed scheme.

The rest of paper is organized as follows. The proposed virtualized small cell networks architecture and the FD self-backhaul mechanism are described in II. The resource allocation problem is formulated in III. Then we divide the
formulated problem into two subproblems and the solution details are described in IV. Simulation results are discussed in V. Finally, we conclude this study in Section VI.

II. SYSTEM MODEL

A. Virtualized Small Cell Network Architecture

We present a virtualized small cell network architecture with \( M \) InPs which deploys and manages a cellular network with one macro cell base stations (MBS) and several self-backhauled small cell base stations (SBSs), and \( N \) MVNOs which provide various services to their subscribers through the same substrate networks. Following the general frameworks of wireless network virtualization [10], the virtualized small cell network architecture consists of three layers: the physical resource layer (PRL), the control and management layer (CML), and the MVNO layer. The PRL, including BSs, spectrum, power and backhauls from different InPs, is responsible for providing available physical resources. Moreover, the PRL also provides CML with the interfaces needed to control resources. The CML virtualizes the physical resources from different InPs and enables the sharing for MVNOs.

Then, the CML manages and allocates the virtual resources to different MVNO users. The resource management functions in CML are realized by a virtual network controller and a virtual resource manager (VRM). The virtual network controller of MVNOs is responsible to collect the resource consumption prices negotiated with InPs, and the users’ information (e.g., payment information and QoS requirements) from MVNOs, then feedback the resource allocation results to MVNOs for the purpose of finishing the settlement between MVNOs and InPs. To maximize the total utility of all MVNOs, the VRM is responsible to dynamically allocate the virtual resources from multiple InPs to different MVNO users. Through the virtualization architecture above, each MVNO can have a virtual network composed of the substrate networks from multiple InPs. Hence each user can get services via different access points (either MBS or SBSs) from different InPs.

We assume that the spectrum bandwidth of the \( m \)-th InP is \( B_m \). The transmit power of the MBS and the transmit power of the SBSs, are \( P_m \) and \( P^s_m \), respectively. \( S_m \) is used to represent the set of SBSs that belong to the \( m \)-th InP. Let \( S^j_m \) be the \( j \)-th SBS in \( S_m \). For ease of presentation, we use \( j \in S_m \) to represent \( S^j_m \in S_m \) in this paper. The set of users of MVNO \( i \) is denoted as \( U_i \). For the users, there are two access choices: MBS or self-backhauled SBS. Those users who are associated to the \( m \)-th MBS is denoted by \( U_m \).

B. Small Cell Self-backhauling Mechanism Based on Full Duplex Communications

In our scheme, SBSs are equipped with FD hardware, which enables them to backhaul data for themselves. In the downlink (DL), a SBS can receive data from the MBS, while simultaneously transmitting to its users on the same frequency band. In the uplink (UL), a SBS can receive data from the users, while simultaneously transmitting data to the MBS on the same frequency band. In this mechanism, the SBS can effectively backhaul itself, eliminating the need for a separate backhaul solution and a separate frequency band. In this paper, we focus on the DL transmission.

To mitigate the interference, we divide the spectrum of InP \( m \) into two parts: \( \alpha_m B_m \) for the MBS and \( (1 - \alpha_m) B_m \) for the SBSs. In DL, the MBS transmits data to not only macro users on \( f_1 \) but also SBSs on \( f_2 \). Similarly, the MBS receives the data from macro users on \( f_1 \) and SBSs on \( f_2 \) in UL. At the same time, SBSs transmit and receive data to their users on \( f_2 \). Obviously, the spectrum indicator vector \( \alpha = (\alpha_1, \alpha_2, ..., \alpha_M) \), which decides the throughput of backhaul and access link, plays an important role in achieving small cell self-backhauls.

For user \( u \in U_i \), the VRM will decide its association BS and allocate some resources to it from the BS. We denote by \( x_{u,m} \) and \( y_{u,m} \) the user’s association indicator and allocated resources ratio (Note that these resources mean time slot resources), respectively. When a user is associated with one BS, \( x_{u,m} = 1 \), otherwise \( x_{u,m} = 0 \). Further, \( j = 0 \) means the user is associated to the \( m \)-th MBS, \( j \neq 0 \) means the user is associated to \( S^j_m \). Similarly, \( y_{u,m,0} \) denotes the resource ratio that the user gets from the \( m \)-th MBS, and \( y_{u,m,j} (j \neq 0) \) denotes the resource ratio that the user gets from \( S^j_m \). Obviously, \( y_{u,m} \) is related to \( x_{u,m} \). Only when \( x_{u,m} = 1 \), \( y_{u,m} \) will be meaningful.

We denote by \( R_{u,m} \) the achievable rate of one user in access DL. For macro users, the achievable link rate can be expressed as \( R_{u,m} = \alpha_m B_m \log \left( 1 + \frac{P_m h_{u,m}}{\sigma^2} \right) \). For small cell users, they suffer co-channel interference from other SBSs in the same InP, so the achievable link rate can be expressed as

\[
R_{u,m,j} = (1 - \alpha_m) B_m \log \left( 1 + \frac{P_m h_{u,m,j}}{\sum_{k \neq j, k \in S_m} P_m h_{u,k} + \sigma^2} \right). \tag{1}
\]

For a given user \( u \), we define \( C_u \) as its overall long-term rate, which can be expressed as follows.

\[
C_u = x_{u,m}^0 \log \left\{ \frac{y_{u,m,0} R_{u,m,0}}{C_u^{m,0}} \right\} + \sum_{j \in S_m} x_{u,m,j} \log \left\{ \frac{y_{u,m,j} R_{u,m,j}}{C_u^{m,j}} \right\}, \tag{2}
\]

where \( C_u^{m,0} \) and \( C_u^{m,j} \) are the overall long-term rates of user \( u \) getting from the \( m \)-th MBS and \( S^j_m \), respectively, log is to guarantee the fairness of the resource allocation [11].

We define the backhaul link rate of \( S^j_m \) by \( R_{m,j}^l \). When the SBS receives data from the MBS, it transmits data to its users at the same time, which results in the self-interference (SI). The value of SI is determined by self-interference cancellation technologies, and is proportional to the transmission power of SBS DL, which could be expressed as \( SI = \delta_m P^m_m \). In addition, a SBS also suffers co-channel interference from other
SBSs because they use the same spectrum $f_2$, so the achievable link rate can be expressed as

$$R_{m,j}^s = (1 - \alpha_m)B_m \log \left(1 + \frac{P_m h_{m,j}^s}{\delta_m P_m^s + \Psi + \sigma^2} \right).$$

where $\Psi = \sum_{k \neq j, k \in S_m}^m P_{k,j}^s$. In each InP, SBSs share the spectrum $f_2$ for backhaul, but the spectrum resource must be divided in time domain or frequency domain (TDD or FDD) to avoid interference. TDD model is adopted in this paper, and we divided the time slot ratio occupied by SBS $z_{m,j}^s$. If we denote by $C_{m,j}^s$ the overall long-term rate of backhaul DL from the $m$-th MBS to $S_{m,j}^s$, it can be expressed as $C_{m,j}^s = z_{m,j}^s R_{m,j}^s$.

### III. PROBLEM FORMULATION

#### A. Utility Function Definition

In our virtualized small cell networks, users pay to their MVNO for getting services. Hence, for a given user $u$, the utility function can be defined as the difference between her/his service rate and the money she/he paid, which is expressed as $G_u = \sum_{m=1}^M C_{m,j}^u - \delta_u$, where $\delta_u$ represents the money user $u$ has paid to its subscribed MVNO. MVNOs purchase resources (including spectrum, time slot, power and backhaul) from InPs to provide services to their users. In this paper, we consider a long-term rate-aware utility function for MVNOs, which is defined as the difference between the total income of all MVNOs earned by serving the users and the total resource consumption cost. For the $i$-th MVNO, its utility can be expressed as:

$$G_i = \sum_{m=1}^M \sum_{u \in U_i} \delta_u C_{m,j}^u - \sum_{m=1}^M \gamma^m T_i^m - \sum_{m=1}^M Q_i^m,$$

where $\gamma^m$ represents the price of the spectrum and power resource, and $\gamma^m$ represents the cost of using the spectrum and power resource, and $\gamma^m$ represents the total utility of all MVNOs. The utility function of the $m$-th InP can be expressed as

$$G_{I,n,P} = \gamma_m^m \sum_{i=1}^N T_i^m + \sum_{i=1}^N Q_i^m - O,$$

where $O$ means the cost of renting or deploying backhaul infrastructure. For simplicity, we assume that all the backhaul income from MVNOs is used to pay for the rent or deployment of backhaul infrastructure in non-self-backhauled small cell networks, which means $\sum O_i^m = O$.

#### B. Virtual Resource Allocation Problem Formulation

In each resource allocation cycle, the VRM needs to dynamically allocate the virtual resources, including MBSs, SBSs, and spectrum, to MVNOs by solving the following optimization problem.

$$\mathcal{P} : \begin{array}{l}
\max_{X,Y,Z,\alpha} G(\alpha, X, Y, Z) \\
\text{s.t. } C_1 : \sum_{u \in U_m}^{x_{m,j}} y_{m,j}^u R_{m,j}^u \leq z_{m,j}^s R_{m,j}^s, j \neq 0. \\
C_2 : x_{m,j}^u \in \{0, 1\}, C_3 : \sum_{m=1}^M \sum_{j=0}^N x_{m,j}^u \leq 1, \\
C_4 : 0 \leq y_{m,j}^u \leq 1 \forall m,j, C_5 : \sum_{u \in U_m}^{x_{m,j}} y_{m,j}^u \leq 1, \\
C_6 : \sum_{u \in U_m}^{x_{m,j}} \leq 1 \forall m,j, C_7 : \sum_{m=1}^N z_{m,j}^s \leq 1 \forall m, \\
C_8 : 0 \leq \alpha_m \leq 1,
\end{array}$$

where $C_1$ indicates the relationship between access DL and backhaul DL of SBSs, $C_2, C_3$ means that each user can only be served either by one MBS or by one SBS, $C_4, C_5$ are the available resource constraints of access DL , $C_6, C_7$ are the available resource constraints of backhaul DL, $C_8$ represents that the spectrum allocation indicator $\alpha_m$ will take a value in the interval of $[0, 1]$.

### IV. DISTRIBUTED VIRTUAL RESOURCE ALLOCATION ALGORITHMS

It can be observed that the considered problem is combinatorial and non-convexity. To reduce the computational complexity, firstly, we assume the spectrum allocation indicator
vector $\alpha$ is fixed, and then we solve $X, Y$ and $Z$ (subproblem 1). Secondly, based on the obtained results of $X, Y$ and $Z$, we solve $\alpha$ (subproblem 2). Furthermore, we come back to first step with the result of $\alpha$ to get the new values of $X, Y$, and $Z$. By iterations like this, the values of $X, Y, Z$ and $\alpha$ will converge, which can be seen as the solution of original problem $\mathcal{P}$. For subproblem 2, due to the fact that the constraints are linear, it’s easy to prove that it is jointly convex with respect to the optimization variables $\{x_m, y_m\}$ by solving the second derivative of the objective function. As a result, we just introduce how to solve subproblem 1 and the whole process of our proposed algorithm in this section.

A. Solving Subproblem 1

For any given spectrum allocation indicator vector $\alpha$, the objective function of $\mathcal{P}$ achieves the optimal solution only when the constraint $C1$ is tight because of the nature of objective function, which means $\sum_{u \in U_m} x_{u}^{m,j} y_{u}^{m,j} R_{u}^{m,j} = z_{m}^{g} R_{m}^{g}, \forall j \in S_{m} \text{ must hold when the objective function gets the maximum value. Based on this theorem, we can get } z_{m}^{g} = \frac{1}{R_{m}^{g}} \sum_{u \in U_{m}^{j}} x_{u}^{m,j} y_{u}^{m,j} R_{u}^{m,j}. \text{Namely, we can replace } Z \text{ in objective function } \mathcal{P} \text{ by } X \text{ and } Y, \text{ which means that the original problem will be transformed from a three variables problem into a two variables problem } \mathcal{P}_{1} \text{ with constraints } C2, C3, C4, C5, C6, C7. \text{ Although problem } \mathcal{P} \text{ has been simplified, the above problem } \mathcal{P}_{1} \text{ is still difficult to solve based on the following observations: (1) The feasible set of } \mathcal{P}_{1} \text{ is non-convex as a result of the binary variables } x_{u}^{m,j}, (2)\text{The objective function is not convex due to the product relationship between } x_{u}^{m,j} \text{ and convex function of } y_{u}^{m,j}. \text{As a result, we first transfer this problem into a convex problem and solve it via a distributed algorithm.}

1) Transferring $\mathcal{P}_{1}$ into convex problem : Following the approach in [11], we relax $x_{u}^{m,j}$ ($j = 0$ is included) in $\mathcal{P}_{1}$ C2 and C3 to be real value variables such that $0 \leq x_{u}^{m,j} \leq 1$. The relaxed $x_{u}^{m,j}$ can be interpreted as the time sharing factor that represents the ratio of time when user $u$ associates to the $m$-th MBS or SBS $S_{m}^{j}$. Then, we define $y_{u}^{m,j} = y_{u}^{m,j} x_{u}^{m,j}, \forall j$ and $x_{u}^{m,j} \log \frac{z_{u}^{m,j} R_{u}^{m,j}}{z_{m}^{g} R_{m}^{g}} = 0$ for $x_{u}^{m,j} = 0$, there exists an equivalent formulation of $\mathcal{P}_{1}$ in (9). The relaxed problem $\mathcal{P}_{1}$ can be recovered by substitution of variable $y_{u}^{m,j} = x_{u}^{m,j} y_{u}^{m,j}$ into problem $\mathcal{P}_{1}$. Based well-known perspective function in convex optimization theory [14], it can be observed that $\mathcal{P}_{1}$ is jointly convex with respect to all optimization variables $x_{u}^{m,j}$ and $y_{u}^{m,j}$.

2) ADMM-based solution algorithm of $\mathcal{P}_{1}$: ADMM [15] is a simple but powerful algorithm that is well suited to distributed convex optimization. Due to constraint $C3'$ in $\mathcal{P}_{1}$, the problem is not separable with respect to different InPs. To apply ADMM to the resource allocation problem $\mathcal{P}_{1}$, this coupling must be handled appropriately. Therefore, we introduce local copy $\tilde{X}_{m}$ of the related global cell association variable $X$ for the $m$-th InP. Roughly speaking, each local variable can be interpreted as the InP’s opinion about the corresponding global variable. Naturally, variables $\tilde{Y}_{m}$ is also local variables for InP $m$, since the InP operates without any limits from other InPs. For the sake of brevity, let us define vector $A_{m} = (\tilde{X}_{m}, \tilde{Y}_{m})$ to represent the local variables of the $m$-th InP. To deal with the constraints, we introduce an indicator function $g(A_{m})$ such that $g(A_{m}) = 0$ when $A_{m} \in \Phi$; otherwise, $g(A_{m}) = +\infty$, where $\Phi$ represents the feasible set of problem $\mathcal{P}_{1}$. With these notations above, problem $\mathcal{P}_{1}$ of maximizing $G_{VRM}$ on set $\Phi$ is equivalent to $\mathcal{P}_{1} : \min_{A_{m}} \{-\tilde{G}_{VRM}(A_{m}) + g(A_{m})\} \text{ s.t. } X_{m} - X = 0 \hspace{1cm} (10)$

We apply ADMM for solving the problem in $\mathcal{P}_{1}$ in a distributed way, and the augmented Lagrangian for $\mathcal{P}_{1}''$ can be written as $L_{\rho}(A_{m}, X) = G_{VRM}(A_{m}) + \lambda_{m}(X_{m} - X) + \frac{\rho}{2} \sum_{m=1}^{M} \|X_{m}^{+} - X\|_{2}^{2} \hspace{1cm} (11)$

where $\rho \in [0, +\infty]$ is a positive constant parameter for adjusting the convergence speed of the ADMM. The ADMM method consists of sequential optimization phases over the primal variables followed by the method of multipliers update for the dual variables. By applying the ADMM to the problem in $\mathcal{P}_{1}$, we first minimize the augmented Lagrangian in (11) over the local variables, then over the global variables, and finally, perform the dual variable update. After several iterations, the values of $X_{m}^{+}$ will close to $X$ and they can be recover to be $0 - 1$ integer according to the method in [16].

B. The Distributed Virtual Resource Allocation Algorithm

Based on the analysis above, the distributed virtual resource allocation algorithm can be summarized as Algorithm 1. In this algorithm, $\alpha$ is a long time-scale optimization variable, while $X, Y$ and $Z$ are short time-scale optimization variables. In a relatively long period, the InPs do not change the values of $\alpha$, and they solve their corresponding subproblems in parallel in each iteration to optimize their local variables by using local CSI information and transmit their local results to the VRM. Then the VRM collects all the local results and coordinates all the InPs to achieve the global consensus based on the consensus constraint and the regularization function. Upon the convergence of the cell association and resource scheme, the InPs attempt to change the value of $\alpha$ to get the optimal gain, and then the network will start the next round cell association and resource allocation adjustment. By this way, there is no need to exchange CSI information between InPs and VRM, which will reduce the signaling overhead significantly.

V. SIMULATION RESULTS AND DISCUSSIONS

In this section, the effectiveness of our proposed virtualized small cell networks with FD self-backhauls and distributed virtual resource allocation algorithm will be demonstrated by computer simulations. In the simulations, we consider a $1Km \times 1Km$ square area covered by two InPs and two
The distributed virtual resource allocation algorithm

\[ \mathcal{P}_f : \max_{X,Y} \sum_{i=1}^{N} \sum_{m=1}^{M} \sum_{u \in U_i} \delta_u \left\{ x_u m,0 \log \frac{\tilde{y} u m,0 R u m,0}{x_u m,0} + \sum_{j \in S_m} x_u m,j \log \frac{\tilde{y} u m,j R u m,j}{x_u m,j} \right\} \]

\[ - \sum_{i=1}^{N} \sum_{m=1}^{M} \sum_{u \in U_i} \alpha m_0 (\alpha m B m \cdot P m) + w m \sum_{j \in S_m} \tilde{y} u m,j (1 - \alpha m) B m \cdot P m \]

\[ - \sum_{m=1}^{M} \left\{ \sum_{j \in S_m} \frac{1}{R_m} (1 - \alpha m) P m \left( \sum_{u \in U_m} \tilde{y} u m,j R u m,j \right)^{-2} \right\} \]

\[ \text{s.t. } C2' : 0 \leq x_u m,j \leq 1, \forall j, C3' : \sum_{m=1}^{M} \sum_{j=0}^{s_m} x_u m,j = 1, C4' : 0 \leq \tilde{y} u m,j \leq x_u m,j, \text{ } C5' : \sum_{u \in U} \tilde{y} u m,j = 1, \forall m, j \]

\[ C6' : \frac{1}{R_m} \sum_{u \in U_m} \tilde{y} u m,0 R u m,0 \leq 1, \text{ } C7' : \sum_{j \in S_m} \frac{1}{R_m} \sum_{u \in U_m} \tilde{y} u m,j R u m,j \leq 1. \]

Algorithm 1: The distributed virtual resource allocation algorithm

1: Initialization
   a) At each InP, collect channel state information of all users within its coverage;
   b) Initialize \( \alpha_0 = 0.5 \), \( o = 0 \) and a stop criterion threshold \( \xi_1 \) at the VRM;
2: while \( \| G^{o+1}_{VRM} o - G^{o}_{VRM} \|_2 > \xi_1 \)
   Push the value of \( \alpha^o_m \) to the \( m \)-th InP
   Run ADMM-based algorithm to solve subproblem 1
   Update \( \alpha^o \rightarrow \alpha^{o+1} \) based on the result of \( X^*, Y^* \) via solving subproblem 2
3: Output the optimal resource allocation scheme \( X^*, Y^*, Z^* \) and \( \alpha^* \)

Fig. 1: The total utility of MVNOs.

Fig. 2: The total utility of InPs.

MVNOs. In each InP, there are one macro BS and four SBSs. Each MVNO owns some subscribed users. The available bandwidth of both of the two InPs are 10 MHz. The transmit power of the macro BS and the transmit power of the SBS are 46 dBm and 20 dBm, respectively. The augmented Lagrangian parameter \( \rho \) is set to 5 \( \times \) 10^7, and the small cell discounting price \( w \) is set to 10^-3.

We evaluate the performance of the proposed virtualized small cell networks with self-backhauls by comparing the following schemes: (a) A traditional small cell network without FD self-backhaul and virtualization [17]; (b) a small cell network with virtualization but without FD self-backhaul [18]; (c) a small cell network with FD self-backhaul but without virtualization [19]. Each scheme has the similar system configurations as described above.

In Figs. 2-4, we compare the utility of MVNOs, users, and InPs with different schemes with\( \delta_u = 10^6 \) and \( \gamma_i = 0.5 \). As shown in the figures, the scheme with FD self-backhaul always outperforms the schemes without FD self-backhaul. This is because the proposed scheme with FD self-backhaul is able to reduce the cost of backhaul and improve the SBS utility ratio, which means that MVNOs can get more available resources at a lower price. As a result, utility values of MVNOs and users are improved. For InPs, the more users...
access to SBSs, the more backhaul revenue they will get in the small cell network with self-backhaul. Furthermore, there is appreciable performance gain of our proposed scheme compared to traditional schemes without virtualization. The reason is that, with infrastructure virtualization, a user is able to connect to a better access point with better channel conditions and lower resource consumption price. That is to say, access point selection gain and spectrum selection gain can be obtained from our proposed virtualized small cell networks.

In addition, as shown in Figs. 2-4, with the growth of the number of users, the total utility of MVNOs increases linearly, the average utility of users decreases slowly, and the total utility of InPs will increase, but the increase rate becomes more and more slow. Because MVNOs have to pay money to InPs for using resources, the VRM only allocates optimal resource amount to users rather than all resources. As a result, the total utility of MVNOs will grow since more users will bring more income, and the total utility of InPs will also go up due to the fact that more resources are consumed. Meanwhile, the average utility of users will descend because some users with bad channel condition access to the network. However, when the number of users is large enough, the ratio of users with bad channel condition will increase and the average link rate of users will decrease accordingly. Considering the resource consumption price, the VRM will not allocate more resources to users because the service rate gain will be lower than the cost of consuming resources. So, the total utility of InPs will grow no more. Nevertheless, the total utility of MVNOs will keep increasing because of the multi-user diversity gain. This is also the reason why the average utility of users does not decline sharply.

VI. CONCLUSION AND FUTURE WORK

In this paper, we first introduced the idea of wireless network virtualization into small cell networks, and proposed a virtual resource management architecture, where radio spectrum, time slots, MBSSs, and SBSs are virtualized as virtual resources. After virtualization, users can access to different InPs to get performance gain. In addition, we proposed to use FD communications for small cell backhauls. Furthermore, we formulated the virtual resource allocation problem as an optimization problem by maximizing the total utility of MVNOs. Simulation results showed that the effectiveness of the proposed scheme. Future work is in progress to consider information-centric wireless network virtualization [20].

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