Energy-Efficient Virtual Resource Allocation in OFDMA Systems

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***Abstract*—Optimization of resource allocation is fundamental to implement orthogonal frequency division multiple access (OFDMA), which energy efficiency (EE) is very much desired. Wireless network virtualization recently emerges to flexibly enable high data rate services, but optimal cross-layer design with OFDMA remains open. While energy efficiency (EE) is a critical issue for OFDMA systems, the appropriate energy efficient design to enable emerging virtualization in wireless OFDMA networks remains open. In this paper, we focus on energy efficient subcarrier and power allocation with wireless network virtualization. To minimize power consumption and to maximize data rate, such virtual resource allocation can be modeled as a non-convex optimization of EE. Exploiting the non-convex fractional programming, we reformulate into a subtractive form as the equivalent optimization. We therefore obtain the iterative algorithm to achieve the optimality. In particular, subcarrier allocation, power allocation, and operator selection in each iteration can be derived by the Lagrange dual decomposition method. Simulations verify that the algorithms can significantly enhance EE in wireless network virtualization architecture.**

***Index Terms*—Wireless network virtualization, energy efficiency, subcarrier assignment, power allocation**

I. Introduction

Current management and operation schemes may not be able to deal with the increasing demands of end-user applications. For example, it is becoming common to use virtual network applications to simultaneously share a game in different parts of world. This emerging virtualization technology is becoming very popular in mobile communications, but it poses many new challenges [1].

In traditional wireless network virtualization, the internet service provider is decoupled in two parts, i.e. the mobile network operator (MNO) and mobile virtual network operator (MVNO) [2]. The MNO owns and operates the physical infrastructure, including the radio access network (RAN). In contrast, the MVNO is generally not related to the physical substrate and/or the spectrum resource. Hence, multiple MVNOs sharing the physical substrate and the spectrum resource. This model fits the concept of XaaS in cloud computing [3].

Many works, so far, have been carried out on network virtualization (NV). They mainly focus on the following five aspects, including high level architecture, isolation, mobile management and resource allocation [4]-[7]. N. M. K Chowdhury*et al.* investigated the state of the art in NV, and presented a new architecture [4]. The authors in [5] proposed algorithms to coordinate the node and the link mapping, while the authors in [6] proposed a dynamic resource pooling and trading mechanism for NV. The research in [7] found an Equilibrium point between MNO and wireless service providers.

In spite of excellent research on wireless network virtualization, limited efforts have been put on the critical EE performance metric. Under the ecology and environmental concerns, EE becomes a critical consideration in future cellular systems [8]-[12]. The authors in [8] developed an EE optimization scheme for interference-limited OFDM wireless communications, while the authors in [9] devised an iterative algorithm to maximize the system EE in device-to-device (D2D) communications. The authors in [10] studied the power efficiency in the relay cellular networks. With both resource assignment and power allocation into account, the research in [11] maximized EE by developing a low-complexity and sub-optimal algorithm. The authors in [12] transformed the EE resource allocation with fairness optimization problem.

Motivated by the aforementioned work, we investigate the joint optimization problem of the subcarrier assignment and power allocation to maximize the EE performance in OFDMA systems. This problem is challenging due to its non-convex objective. Particularly, the MNO/MVNOs association strategy should be enhanced from the traditional single operator strategy. Compare with the existing literature, there are three major contributions made in this work:

1) We optimize EE in the cross-layer OFDMA and the NV. In practical applications, MNO own subscribers. So we proposed a virtual resource allocation model, considering one MNO and mutiple MVNOs. Besides, the subcarrier allocation, power allocation and operator selection are defined respectively.
2) An EE optimization problem in the OFDMA system is formulated as a non-convex one. The considered non-convex problem in fractional form is transformed into an equivalent optimization problem in subtractive form with tractable solution.
3) We evaluate the EE performance gain of virtualization and the corresponding resource allocation optimization solution. The proposed scheme enhances the EE performance about 50 percent in the system.

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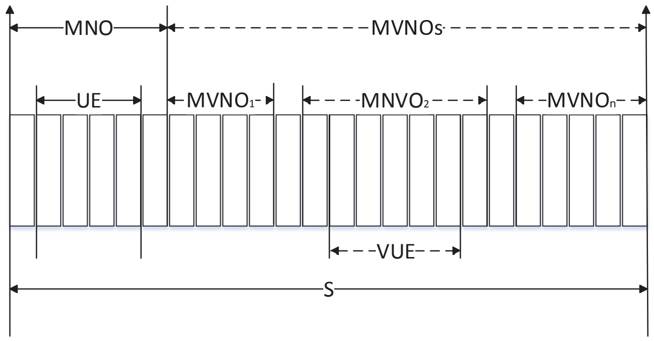

Fig 1: A DL frame structure sample in OFDMA systems with virtual resource allocation

II. System Model and Problem Formulation

A. System Model

Let's consider a single-cell downlink (DL) OFDMA system with wireless network virtualization, consisting of one unique MNO, as in [1]. The infrastructure and spectrum resources can be abstracted and sliced into multiple virtual slices by the MNO. These virtual slices are leased to $s_1 (s_1 \geq 1)$ MNVOs. The MVNOs assign the virtual resource to wireless service providers. A wireless virtualization controller is responsible for collecting the information from MVNOs and then feedback the resource allocation. In the system above, the assumptions are in the following:

- The DL transmissions share the spectrum resource using FDD mode.
- In a cell served by infrastructure provider (InP), the total downlink bandwidth B Hz is divided into S subcarriers and each subcarrier has a bandwidth of B/S.
- We assume that each subcarrier is isolated and can be assigned to at most one link.
- The MNO and MVNOs $(1, 2, ..., n)$ hold K_n UEs, where K represents all the active UEs in the system.

Base on the assumptions, Fig.1 shows a DL frame structure sample in OFDMA systems. Let us represent $g_{k,s}$ and $h_{k,s}$ as the channel power gain and the frequency response for the link k on subcarrier s, respectively. We assume that a UE will spread the available power as $p_{k,s}$ for the link k on subcarrier s, and that the power spectrum density (PSD) of the additive white Gaussian noise at the BS is $n_0/2$. Then, the achievable data rate $r_{k,s}$ of link k on subcarrier s (in unit of bit/Hz/s) can be given by

$$r_{k,s} = \log_2(1 + p_{k,s} g_{k,s}), \tag{1}$$

and the channel power gain $g_{k,s}$ can be expressed by

$$g_{k,s} = \frac{|h_{k,s}|}{(\frac{B}{S})n_0}. \tag{2}$$

Based on Eq. (1) and (2), the total transmission rates and transmission power for MNO on link k are respectively given by

$$R_k^m(X,P) = \sum_{s=1}^{s_0} x_{k,s} r_{k,s}\,, \forall k, \tag{3}$$

and

$$P_k^m(X,P) = \sum_{s=1}^{s_0} x_{k,s} p_{k,s}\,, \forall k. \tag{4}$$

Note that here after, $P = (p_{k,s})$ represents the power set, and $X = (x_{k,s})$ is the subcarrier allocation variable, with $x_{k,s}$ being an indicator variable that is 1 if subcarrier is allocated to link k and 0 otherwise.

Similarly, the total transmission rates and transmission power for MVNO on link k are respectively expressed by

$$R_k^v(X,P) = \sum_{s=s_0+1}^{s_0+s_1} x_{k,s} r_{k,s}, \forall k, \tag{5}$$

and

$$P_k^v(X,P) = \sum_{s=s_0+1}^{s_0+s_1} x_{k,s} p_{k,s}, \forall k. \tag{6}$$

where s_0 and s_1 express the subcarrier owned by MNO and MVNO, respectively.

Accordingly, P_k^c denotes the circuit power consumption for each base station, and λ denotes the power efficiency [13]. The power consumption of link k is modeled as

$$PC_k(X,P) = \lambda P_k(x,p) + P_k^c, \forall k. \tag{7}$$

Based on Eqn. (3), (5) and (7), the total transmission rates and transmission power for MNO on link k are respectively expressed by

$$R(X,P) = \sum_{k=1}^{K} R_k^m(X,P) + \sum_{k=1}^{K} R_k^v(X,P), \forall k, \tag{8}$$

and

$$P(X,P) = \sum_{k=1}^{K} PC_k^m(X,P) + \sum_{k=1}^{K} PC_k^v(X,P), \forall k. \tag{9}$$

Then, the link EE of MNO and MVNO can expressed by

$$\eta_k^{EE,m}(X,P) = \frac{R_k^m(X,P)}{PC_k^m(X,P)}, \forall k, \tag{10}$$

and

$$\eta_k^{EE,v}(X,P) = \frac{R_k^v(X,P)}{PC_k^v(X,P)}, \forall k. \tag{11}$$

and the systems EE can be given by

$$\eta(X,P) = \frac{R(X,P)}{P(X,P)}. \tag{12}$$

B. Problem Formulation

Base on the above assumptions and considerations, we can formulate the optimization of the worst case link EE in the considered OFDMA systems as

$$\max_{X,P} \min_{k} (\alpha_k \eta_k^{m,EE} + (1-\alpha_k)\eta_k^{v,EE})$$

$$\begin{aligned}
\text{s.t.} C1 &: \sum_{s=1}^{s_0} x_{k,s} r_{k,s} \geq R_k^{req} \& \sum_{s=s_0}^{s_0+s_1} x_{k,s} r_{k,s} \geq R_k^{req}, \forall k \\
C2 &: \sum_{k=1}^{k} x_{k,s} \leq 1, \forall s \\
C3 &: \sum_{k=1}^{K} \sum_{s=1}^{s_0} x_{k,s} p_{k,s} \leq P_k^{\max} \\
&\& \sum_{k=1}^{K} \sum_{s=s_0}^{s_0+s_1} x_{k,s} p_{k,s} \leq P_k^{\max}, \forall k \\
C4 &: \alpha_k \in \{0,1\}, \forall k \\
C5 &: P_{k,s} \geq 0, \forall k, n \\
C6 &: x_{k,s} \in \{0,1\} \forall k, n,
\end{aligned} \tag{13}$$

where R_k^{req} is the rate request of UE, and P_k^{max} is the maximum power limit that the base station can provide, respectively. The optimization objective is to maximize the worst-case link EE, while C1 specify the rate requirements of users, C3 is the peak transmission power limitation, C2 and C6 ensure that each subcarrier can be only allocated to one UE, and the variable α_k in constraint C4 ensure that each UE can only access one MNO or MVNO.

III. Joint Resource Allcation and Power Control Scheme

A. Problem Reformulation

The problem given in Eqn. (13) is known as a mixed-integer nonlinear programming (MINLP) Problem. The constraints C4 and C6 contain two binary variables α_k and $x_{k,s}$. The other constraint includes variable $p_{k,s}$. For transforming the nonconvex problem, Φ denotes the feasible domain defined by C1-C6, and η_{EE}^* denotes the maximum worst-case link EE. Then, we can get

$$\begin{aligned}
\eta_{EE}^* &= \max_{\{X,P\}\in\phi} \min_k (\alpha_k \frac{R_k^m(X,P)}{PC_k^m(X,P)} + (1-\alpha_k)\frac{R_k^v(X,P)}{PC_k^v(X,P)}) \\
&= \min_k (\frac{R_k'(A^*,X^*,P^*)}{PC_k'(A^*,X^*,P^*)}),
\end{aligned} \tag{14}$$

where A^*, X^*, P^* form the optimal solution of Eqn. (13). We are now ready to give following proposition.

Proposition 1: The maximum EE η_{EE}^* is achieved if and only if

$$\begin{aligned}
&\min_k [R_k(A^*,X^*,P^*) \\
&\quad - \eta_{EE}^* PC_k(A^*,X^*,P^*)] = 0.
\end{aligned} \tag{15}$$

The proof comes from straightforward extension of the generalized fractional programming theory [14].

B. Iterative Algorithm for EE Maximization

It can be shown from Theorem 1 that we can solve Eqn. (13) via its equivalent objective Eqn. (15) known as the Dinkelbach method [16]. Let g denote the number of iterations, and ε denote the tolerance threshold. Then, the iterative optimal EE algorithm can be summarized in Algorithm 1.

The transformed problem $G(\eta_{EE})$ is a mixed combinatorial and non-convex optimization problem. In order to derive an ideal EE algorithm, we solve the above problem in two steps.

Algorithm 1 Iterative Energy Efficiency Optimal Algorithm

Require:

•$Step1$: Initialization: $g = 0$, $\eta_{EE} = 0$;
Set the maximum iteration number $G_{\max}$;

•$Step2$: Solve the problem in (13) for a given η_{EE} and obtain (A', X', P'):

$$\begin{aligned}
G(\eta_{EE}) = \max_{\{X,P\}\in\phi} \min_k &[R(A^*,X^*,P^*) \\
&- \eta_{EE} PC(A^*,X^*,P^*)]
\end{aligned}$$

•$Step3$: Set $\eta_{EE} = \min_k \frac{R_k'(A',X',P')}{PC_k'(A',X',P')}$. If $|G(\eta_{EE})| > \varepsilon$, set $g = g+1$;

•$Step4$: Repeat steps 2-3 until $|G(\eta_{EE})| < \varepsilon$ or $g > G_{\max}$;

Ensure:

return η_{EE}^*;

$Step1$ $(smooth\ the\ curve)$: In the first step, we smooth the originally non-smooth optimization problem through a new variable π. The corresponding optimization problem can be written in the following equivalent form

$$\begin{aligned}
\max_{A,X,P} \quad & \pi \\
& \text{s.t. } C1, C2, C3, C4, C5, C6 \\
& C7 : R_k'(A,X,P) - \eta PC_k'(A,X,P) \geq \pi, \forall k.
\end{aligned} \tag{16}$$

Regarding the property of π and proposition 1, we find that $\pi \geq 0$ for all feasible X, A and P. However, the problem given in Eqn. (16) is still a MINLP problem for a given η. The total number of possible combinations in the algorithm is $O(K^N)$. It shall be improved for the fast-changing channel state.

$Step2$ $(Constraint\ Relaxations)$: In the second step, we relax the combinatorial constraints in C4 and C6 such that the corresponding variables are $0 \leq \alpha_k \leq 1$ (this can be interpreted as a possibility that UE k choose MNO or MVNO) and $0 \leq x_{k,s} \leq 1$ (this can be seen as a sharing factor of link k using the subcarrier n). Specifically, we introduce an auxiliary variable, and define it as $M = (m_{k,s}) = (X_{k,s} P_{k,s})$.

After the constraint relaxation, the optimization problem Eqn. (16) can be formulated as

$$\begin{aligned}
\max_{A,X,P} \quad & \pi \\
\text{s.t. } & C1, C2, \\
& C3 : \sum_{k=1}^{K} \sum_{s=1}^{s_0} m_{k,s} \leq P_k^{\max} \& \sum_{k=1}^{K} \sum_{s=s_0}^{s_0+s_1} m_{k,s} \leq P_k^{\max}, \forall k \\
& C4 : m_{k,s} \geq 0, \forall k, n \\
& C5 : x_{k,n} \in [0,1], \forall k, n \\
& C6 : a_k \in [0,1], \forall k \\
& C7 : R_k'(A,X,P) - \eta PC_k'(A,X,P) \geq \pi.
\end{aligned} \tag{17}$$

In addition, the optimization problem in Eqn. (17) is jointly convex in A, X, M and π, as proved in Appendix A. Upon rearranging terms, the Lagrangian can be formulated as

$$L(A, X, M, \pi, \varphi_1, \varphi_{1'}, \varphi_2, \varphi_3, \varphi_{3'}, \varphi_4), \tag{18}$$

where $\varphi_1 \geq 0, \varphi_{1'} \geq 0, \varphi_2 \geq 0, \varphi_3 \geq 0, \varphi_{3'} \geq 0$, and $\varphi_4 \geq 0$ are the Lagrange multipliers corresponding to the required minimum capacity constraint C1, maximum transmission power constraint C3 and smooth function constraint C7, respectively. In particular, we substitution $M = (m_{k,s}) = (X_{k,s}P_{k,s})$ in Eqn. (18).

Thus, the lagrangian dual function of (18) can be expressed as

$$\begin{aligned} &D(\varphi_1, \varphi_{1'}, \varphi_2, \varphi_3, \varphi_{3'}, \varphi_4) \\ &= \max_{\{A,X,M,\pi\} \in \{C4-C6\}} L(A, X, M, \pi, \varphi_1, \varphi_{1'}, \varphi_2, \varphi_3, \varphi_{3'}, \varphi_4). \end{aligned} \tag{19}$$

Since Eqn. (13) is transformed into a concave optimization problem after step 1 and step 2, the Karush-Kuhn-Tucker (KKT) conditions are the necessary and sufficient conditions for the optimal solutions. To simplify Eqn. (19), we maximize the optimization problem by solving the following three sub-problems.

1) Subcarrier Assignment and Power Allocation: For a given subcarrier assignment x, the first sub-problem can be expressed as

$$\begin{aligned} &\max L(X, M) \\ &\text{s.t.} C4, C5 \end{aligned} \tag{20}$$

Thus, from Eqn. (20), the power allocation policies can be obtained as

$$P^*_{k,s} = \frac{m^*_{k,s}}{x_{k,s}} = [w^*_{n,k} - \frac{1}{g_{k,s}}]^+, \forall k, n, \tag{21}$$

where $[x]^+ = \max\{x, 0\}$, and the water-filling level $w^*_{k,s}$ is derived as

$$w^*_{k,s} = \frac{\varphi^k_1 + \varphi^k_{1'} + \varphi^k_4}{(\varphi^k_3 + \varphi^k_{3'} + \eta\varphi^k_4)ln2}. \tag{22}$$

Substituting the optimal power allocation Eqn. (21) into (20), we can obtain the optimal subcarrier assignment as

$$x^*_{k,s} = \begin{cases} 1, & k = \arg\max\limits_{1 \leq k \leq K} H_{k,s} \\ 0, & otherwise, \end{cases} \tag{23}$$

where

$$H_{k,s} = \left(\varphi^k_1 + \varphi^k_{1'} + \varphi^k_4\right) [\log_2 w_{k,s}g_{k,s}]^+ - \frac{1}{\ln 2}[1 - \frac{1}{w_{k,s}g_{k,s}}]^+, \tag{24}$$

2) Operator A and smooth variable π selection: On the one hand, we take the partial derivative of Eqn. (17) by with respect to α_k, and have

$$\frac{\partial L}{\partial \alpha_k} = \varphi^k_4(R^m_k(X, M)P^v_k(M) - R^v_k(X, M)P^m_k(M)), \tag{25}$$

for all UEs k. KKT conditions specify that

$$\frac{\partial L}{\partial \alpha^*_k} \begin{cases} < 0, & \alpha^*_k = 0 \\ = 0, & 0 < \alpha^*_k < 1 \text{ }, \forall k \\ > 0, & \alpha^*_k = 1. \end{cases} \tag{26}$$

Substituting the optimal power allocation (25) into (26), we further obtain

$$\alpha^*_k = \begin{cases} 1, & I_k > 0 \\ 0, & I_k < 0, \end{cases} \tag{27}$$

where

$$\begin{aligned} I_k = &\sum_{s=1}^{s=s_0} m^*_{k,s} \log_2(1 + \tfrac{m^*_{k,s}g_{k,s}}{x^*_{k,s}})(\lambda \sum_{s=s_0+1}^{s=s_0+s_1} m^*_{k,s} + P^c_k) \\ &- \sum_{s=s_0+1}^{s=s_0+s_1} m^*_{k,s} \log_2(1 + \tfrac{m^*_{k,s}g_{k,s}}{x^*_{k,s}})(\lambda \sum_{s=1}^{s=s_0} m^*_{k,s} + P^c_k). \end{aligned} \tag{28}$$

In addition, set $X^* = (x^*_{k,s})$ and $M^* = (m^*_{k,s})$, which can be obtained from Eqn. (21) and (23).

On the other hand, we have

$$\begin{aligned} &max(1 - \sum_{k=1}^{K} \varphi^k_4)\pi \\ &\text{s.t.} 0 \leq \pi \leq \sum_{k=1}^{K} \varphi^k_4((1 - \alpha_k)P^m_k(M)R^v_k(X, M) \\ &\qquad + \alpha_k P^v_k(M)R^m_k(X, M) - \eta P^v_k(M)P^m_k(M)), \end{aligned} \tag{29}$$

for all UEs k. From (29), the smooth variable π selection takes the following form

$$\pi^* = \begin{cases} 0 & \sum\limits_{k=1}^{K} \varphi^k_4 > 1 \\ F^*_{k,s}, & \sum\limits_{k=1}^{K} \varphi^k_4 \leq 1, \end{cases} \tag{30}$$

where

$$\begin{aligned} F^*_{k,s} = &\min_k\{((1 - \alpha^*_k)P^m_k(M^*)R^v_k(X^*, M^*) \\ &+ \alpha^*_k P^v_k(M^*)R^m_k(X^*, M^*) - \eta P^v_k(M^*)P^m_k(M^*))\}. \end{aligned} \tag{31}$$

3) Subgradient Method: Thus, the subgradient-based method [13] can be utilized to solve the dual problem in Eqn. (19). The subgradient of the dual fuction can be given as

$$\nabla\varphi^k_1 = \sum_{s=1}^{s_0} m^*_{k,s}\log_2(1 + \frac{m^*_{k,s}g_{k,s}}{x^*_{k,s}}) - R^{req}_k, \tag{32}$$

$$\nabla\varphi^k_{1'} = \sum_{s=s_0+1}^{s_0+s_1} m^*_{k,s}\log_2(1 + \frac{m^*_{k,s}g_{k,s}}{x^*_{k,s}}) - R^{req}_k, \tag{33}$$

$$\nabla\varphi^k_3 = P^{\max}_k - \sum_{s=1}^{s_0} m^*_{k,s}, \tag{34}$$

$$\nabla\varphi^k_{3'} = P^{\max}_k - \sum_{s=s_0+1}^{s_0+s_1} m^*_{k,s}, \tag{35}$$

$$\begin{aligned} \nabla\varphi^k_4 = &(1 - \alpha^*_k)P^m_k(M^*)R^v_k(X^*, M^*) \\ &+ \alpha^*_k P^v_k(M^*)R^m_k(X^*, M^*) - \eta P^v_k(M^*)P^m_k(M^*) - \pi, \end{aligned} \tag{36}$$

for all UEs k. The gradient method leads to the following update equations

$$\nabla\varphi^k_q(t + 1) = [\nabla\varphi^k_q(t) - \alpha_q(t)\nabla\varphi_q(t)]^+, \tag{37}$$

where $q \in \{1, 1', 3, 3', 4\}$, $\nabla\varphi^k_q(t)$ denotes the subgradient utilized in the t th inner-loop iteration, and $\alpha_q(t)$ is the positive step size.

$$
\begin{aligned}
&L(A, X, M, \pi, \varphi_1, \varphi_{1'}, \varphi_2, \varphi_3, \varphi_{3'}, \varphi_4) \\
&= \pi + \sum_{k=1}^{K} \varphi_1^k (R_k^m(X, M) - R_k^{req}) + \sum_{k=1}^{K} \varphi_{1'}^k (R_k^v(X, M) - R_k^{req}) + \sum_{s=1}^{s_0+s_1} \varphi_2 (1 - \sum_{k=1}^{k} x_{k,s}) \\
&\quad + \sum_{k=1}^{K} \sum_{s=1}^{s_0} \varphi_3^k (P_k^{\max} - \sum_{k=1}^{k} \sum_{s=1}^{s_0} m_{k,s}) + \sum_{k=1}^{K} \sum_{s=s_0+1}^{s_0+s_1} \varphi_{3'}^k (P_k^{\max} - \sum_{k=1}^{k} \sum_{s=s_0+1}^{s_0+s_1} m_{k,s}) \\
&\quad + \sum_{k=1}^{K} \varphi_4^k ((1-\alpha_k) P_k^m(M) R_k^v(X, M) + \alpha_k P_k^v(M) R_k^m(X, M) - \eta P_k^v(M) P_k^m(M)) - \pi).
\end{aligned} \tag{18}
$$

Algorithm 2 Subgradient-based Energy Efficiency Optimal Algorithm

- Set the iteration indices: $t = 0, n = 0$, maximum number of iterations t_{max}, n_{max}
- Initialize the lagrange multipliers φ_q, the positive step size α_q and the energy efficiency policies P_t, X_t, A_t, π_t for $t = 0$

repeat
  repeat
    Solve the power allocation and subcarrier allocation by using Eqn. (21) and (23). Assign the solutions to P_t and X_t
    Solve the operator and π selection by using Eqn. (28) and (31). Assign the solutions to X_t and π_t; $t = t + 1$
  until Convergence = **true** or $t > t_{max}$
  Update $\alpha_q(t)$ by subgradient method ; $m = m + 1$
until Convergence = **true** or $n > n_{\max}$
return $\{P_t, X_t, A_t, \pi_t\}$ as $\{\mathrm{P}^*, \mathrm{X}^*, \mathrm{A}^*, \pi^*\}$;

IV. Results and Discussions

In this section, we present system simulation results to evaluate the performance of the proposed optimization. In the simulation, we consider a cell with radius of 1km. There are $S = 128$ subcarriers in the system. We set $s_0 = 32$ in MNO. We assume a total system bandwidth of $B = 5$ MHz and a noise density of $n_0 = -174$ dB/HZ. A 3GPP path loss model model is considered as $34.5 + 35\log_{10}(d)$ with a reference distance of $d_0 = 60m$. The number of simulation samples is 2000. In all samples, the fast-fading coefficients are all generated as i.i.d. Rayleigh random variables with unit variances. We assume that the static circuit power consumption of P_c is 40 dBm and that the power efficiency is $\lambda = 3$. The data rate requirement of each UE is set at 80 kbit/s and the total transmission power is 43 dBm.

Fig. 2 illustrates the EE versus the total number of UEs. The performances are compared among three algorithms: the network EE-optimal (NEP) algorithm [10], the fairness EE-optimal (FEP) method [11], and the virtual network EE-optimal (VNEP) with algorithms 1 and 2 proposed in this paper. It can be observed that the EE performs generally decline with the number of UEs since some subcarriers have been occupied by others. It can be seen that the NEP performs about 10 percent better than FEP since it does not consider the fairness of UEs. The VNEP performs about 50 percent better

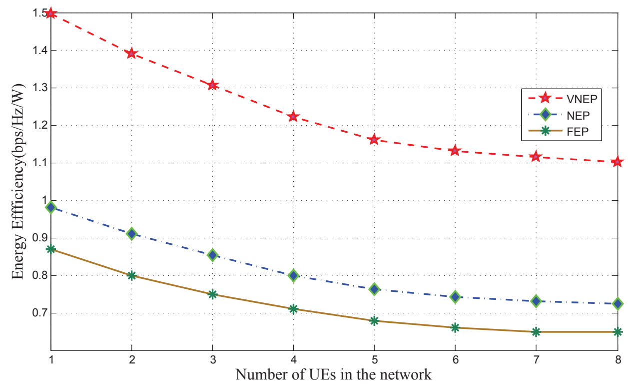

Fig 2: EE Performance vs. UE number in the OFDMA system

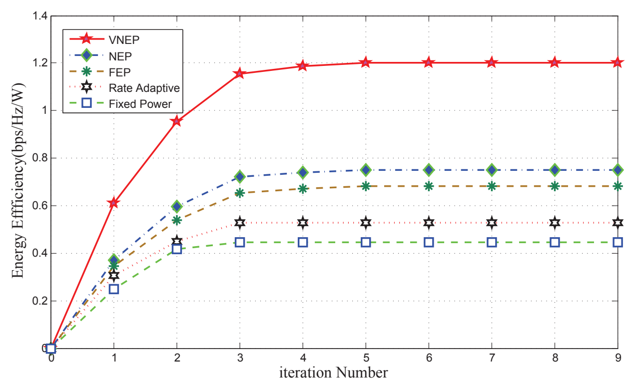

Fig 3: Performance and convergence evolution comparisons among different optimal algorithm

than other solutions due to the gains from the NV architecture. The subcarrier allocation and power control functions is realized by a wireless virtualization controller. The controller is responsible for collecting the downlink state information from MVNOs, and then feedback the subcarrier allocation results to the MVNOs for the purpose of finishing the settlement between them. Besides, UEs in the VNEP can dynamic select the best server provider between MNO and MVNO through variable α.

Fig. 3 depicts the convergence evolution of five different algorithms. Besides the algorithms above, two more algorithms are presented as baselines. The first algorithm perform subcarrier allocation based on the UE rate [15]. The second algorithm is based on a fixed power allocation, i.e., each subcarrier has the same fixed transmission power. It can be observed that the proposed VNEP with algorithms 1 and 2 in this paper performed the best. On the other hand, the rate adaptive and

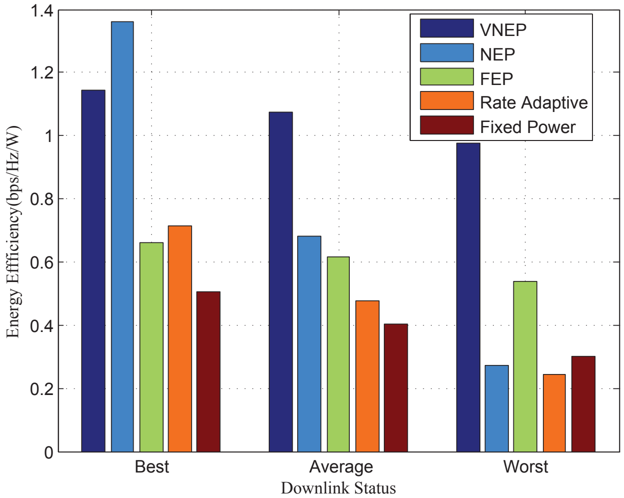

Fig 4: EE performance in different downlink status

power allocation algorithms converged more quickly than the other three EE-optimal algorithms because the two baselines have lower computing complexity.

In Fig. 4, we assume that the UE number is nine. Hence, there are nine kinds of downlink EE performance in the system. We show the performance in three situations: the best downlink, the average downlink, and the worst downlink. It can be observed that while the NEP performs better in terms of average and best cases, it is not very well balance with a poor worst EE. The EE of each downlink is better balanced in the FEP since it considers the fairness of UEs. The proposed VNEP algorithm not only performs the best in the three categories, but also it is well-balanced.

V. Conclusion

In this paper, we proposed an virtual resource allocation in OFDMA systems. In particular, the subcarrier allocation, power allocation, and operator selection have been jointly optimized. To deal with the optimization, a non-convex fractional has been formulated and transformed into a subtractive form. Subsequently, we smooth the curve and find a solution by the Lagrange dual decomposition method. Simulation results have demonstrated a performance gain about 50 percent with virtualization. Future work is in progress to consider energy efficient with delay performance in the proposed scheme.

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Appendix A
Proof of Problem Convergence

By following a similar approach as that presented in [14], we prove the problem convergence in Eqn. (17) with two separated steps.

First, If $g(m)$ is concave, hence its perspective function $xg(\frac{m}{x})$ is concave in (m, x). The function $x_{k,s}log_2(1+\frac{m_{k,s}g_{k,s}}{x_{k,s}})$ can be seen as a perspective function of the concave $log_2(1+m_{k,s}g_{k,s})$. We know the sum of concave functions preserves concavity. C1 and C7 are convex because the super-level set of them is convex.

Second, C2-C6 are all linear constraints. Therefore, the convergence of Eqn. (17) is proved.

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