Hierarchical Matching Game for Service Selection and Resource Purchasing in Wireless Network Virtualization

S. M. Ahsan Kazmi, Nguyen H. Tran, Tai Manh Ho, and Choong Seon Hong

***Abstract*— Wireless network virtualization is identified as one of the key enabling technologies to bring fifth-generation networks into fruition. In this letter, we model the service selection and resource purchasing problem as a two-stage combinatorial optimization problem. To solve this problem, we propose a hierarchical matching game-based scheme, which satisfies the efficient resource allocation and strict isolation requirements. Simulation results show that our proposal outperforms the fixed sharing approach by 32% and achieves up to 97% of performance obtained by the optimal approach (general sharing scheme) in terms of average sum rate.**

***Index Terms*— Matching games, slice allocation, wireless network virtualization.**

I. Introduction

Wireless Network Virtualization (WNV) is a promising candidate to enable the fifth generation (5G) networks [1]. Efficient allocation of physical resources owned by infrastructure providers (InPs) to mobile virtual network operators (MVNOs) users have received significant attention in a single-cell WNV scenario [2]. Note that, InP physical resources are abstracted into isolated virtual resources (slices) which are shared among MVNOs. However, a practical deployment of a WNV involves a multi-cell scenario where the coverage area of a specific region will be serviced by a set of InPs, thus, approaches based on single-cell WNV do not apply and fail. Then, a significant challenge is the efficient allocation of the resources such that the total performance of WNV over a specific region is improved.

Typically resource allocation in WNV can be done either by directly allocating resources from an InP-BS to MVNO users [3], [4] or allocating resources from an InP to a MVNO that further decides the allocation for its users [5]. The former approach is employed by the works in [3] and [4] in which the authors investigate the resource allocation problem in a multi-cell based WNV. However, these work increases the computation complexity of the InPs due to large computations required. Furthermore, since MVNOs are not involved in the resource allocation, the intra-resource customization cannot be achieved, i.e., MVNOs cannot decide how the resources within the slice can be allocated. The works in [5] consider the latter approach that has shown improved user satisfaction, social efficiency and resource utilization. However, the use of auction based game in a multi-cell scenario requires a third party rule-enforcing authority which collects all bids and then allocates resources in a centralized manner. We address these aforementioned challenges by introducing a novel two-level matching algorithm (inspired by [5]) which is designed to separately capture the revenue maximization for both the InP and MVNOs (i.e., at each level) while guaranteeing service contract agreements between the InP and MVNOs. In our model, first, service selection is performed in which users are associated to the MVNOs and then each MVNO is provided slices from InPs to serve its users. By adopting such a model, the computational load of an InPs is reduced (compared to [3], [4]) because now InP is only responsible for allocating resources to each MVNO. In summary, our novelty and contributions include:

We formulate the *service selection* and *resource purchasing* problems in multi-cell WNV with the isolation constraint as a combinatorial optimization problem. To solve this problem, we develop a hierarchal matching algorithm that achieves a near optimal solution and enable distributed implementation.

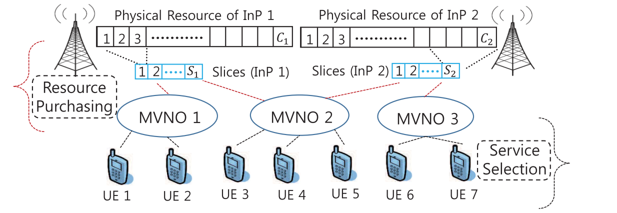

Fig. 1. System model: The InP owns the physical resources, virtualizes them into slices and allocates to multiple MVNOs.

II. System Model and Problem Definition

Consider a downlink network with N base stations (BSs), each owned by an InP as shown in Fig. 1. [1] The InP provides its service to a set of M MVNOs by individual contracts. Moreover, a MVNO $m \in M$ provides its service to a set K_m of user equipments (UEs). Then, $K = \cup_m K_m$ represent the total number of UEs. We use notation $|K|$ to denote the cardinality of a set K.

A. Channel Model and Assumptions

Each InP owns a set of C_n orthogonal channels, each with bandwidth W. We assume static inter-InP interference such that the interference from other InPs is absorbed into the background noise σ^2. Moreover, we assume equal power on every channel of an InP n, i.e., $P_n = \frac{P_n^{max}}{|C_n|}$, where P_n is the power on each channel and P_n^{max} is the maximum power of an InP n. Furthermore, an InP n provides isolated services by a set of S_n slices, where each slice s_n allocated by InP n to MVNOs m will include heterogeneous number of channels based on MVNO's m demand. Then, the data rate for an UE

[1] InPs belong to different vendors that own orthogonal frequency channels through administrative licensing.

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k on a slice s_n of an InP n is:

$$R_{n,k}^{s_n} = \sum\nolimits_{c \in s_n} W \log\left(1 + \gamma_{n,k}^{c}\right), \quad (1)$$

where $\gamma_{n,k}^{c} = \frac{P_n g_{n,k}^{c}}{\sigma^2}$, $g_{n,k}^{c}$ represents the channel gain between InP-BS n and UE k on channel c of slice s_n.

B. Problem Formulation

WNV aims to fulfill the objectives of all UEs, MVNOs and InPs. Each UE $k \in K$ chooses its service by:

$$\textbf{UE}: \min_{x_{k,m} \in \{0,1\}} \sum\nolimits_{m \in M} x_{k,m} \beta_m^M d_k, \quad (2)$$

$$\text{s.t.} \sum\nolimits_{m \in M} x_{k,m} = 1, \quad (3)$$

where $x_{k,m} \in \boldsymbol{X}$ is the variable with $x_{k,m} = 1$ indicating that UE k proposes to MVNO m for service selection and $x_{k,m} = 0$ otherwise, d_k is the demand of the UE k, and β_m^M is the per unit price of MVNO m. Minimizing (2) achieves the UE's goal to pay the minimum and the constraint in (3) represents that a UE can be serviced by only one MVNO. Next, each MVNO m aims to serve its UEs with the least cost and optimize its bandwidth according to the slice price offered by the InP.

$$\textbf{MVNO}: \max_{\tilde{x}_{k,m}, \tilde{y}_{m,n}^{s_n} \in \{0,1\}} \sum\nolimits_{k \in K} \tilde{x}_{k,m} \beta_m^M d_k - \sum\nolimits_{n \in N} \sum\nolimits_{s_n \in S_n} \tilde{y}_{m,n}^{s_n} \beta_n^I |s_n|, \quad (4)$$

$$\text{s.t.} \sum\nolimits_{m \in M} \tilde{x}_{k,m} \leq 1, \ \forall k, \quad (5)$$

$$\sum\nolimits_{k \in K} \tilde{x}_{k,m} l_{k,n} \leq \tilde{y}_{m,n}^{s_n} |s_n|, \quad \forall n, \quad (6)$$

where $\tilde{x}_{k,m} \in \tilde{\boldsymbol{X}}$ is the decision variable with $\tilde{x}_{k,m} = 1$ indicating that UE k proposal is accepted by MVNO m, $\tilde{y}_{m,n}^{s} \in \tilde{\boldsymbol{Y}}$ is the variable with $\tilde{y}_{m,n}^{s_n} = 1$ denoting that MVNO m proposes to buy slice s_n of InP n and $\tilde{y}_{m,n}^{s_n} = 0$ otherwise. β_n^I is the InP n's per unit price, and $l_{k,n}$ is the required channels to fulfill d_k on InPs n which is calculated by MVNO (details in Sec. III-A). Moreover, (5) ensures that k is serviced by at most one MVNO and (6) ensures that the allocated resources on slice are less than the capacity of slice provided to a MVNO m.

Finally, the InP aims to satisfy MVNOs' demand such that the contracts agreements are not violated:

$$\textbf{InP}: \max_{y_{m,n}^{s_n} \in \{0,1\}} \sum_{m \in M} \sum_{s_n \in S_n} y_{m,n}^{s_n} \Big(\sum_{k \in K_m} \log(R_{n,k}^{s_n}) + \omega \beta_n^I |s_n| \Big) \quad (7)$$

$$\text{s.t.} \sum\nolimits_{m \in M} \sum\nolimits_{s_n \in S_n} y_{m,n}^{s_n} \leq |S_n|, \quad (8)$$

$$\sum\nolimits_{k \in K_m} \sum\nolimits_{s_n \in S_n} y_{m,n}^{s_n} R_{n,k}^{s_n} \geq d_m, \quad \forall m, \quad (9)$$

where $y_{m,n}^{s_n} \in \boldsymbol{Y}$ is the decision of InP with $y_{m,n}^{s_n} = 1$ indicating that InP n accepts the slice s_n buying proposal of MVNO m and d_m represents the UE demand of the MVNO m (i.e., $d_m = \sum_{k \in K_m} d_k$). The objective function in (7) represents the proportional fairness among UEs' [7] and InP revenue in the first and second term, respectively. ω is a weight characterizing the trade-off between fairness and InP's revenue. Through (8) we ensure that allocated slices are less than total InP slices and (9) ensures the contract agreement that also reflects the isolation among MVNOs. Isolation is the fundamental requirements of WNV and we consider it at the physical resource level, i.e., channels. [5].

Unfortunately, the problem that optimizes the objectives of all UEs, MVNOs and InPs is a mix integer linear programming problem, which is NP-hard due to its combinatorial nature [6]. Obtaining a central solution (e.g., using exhaustive search) for this problem incurs: i) heavy computational workload, and ii) privacy issues between UEs, MVNOs and InPs. Therefore, by using matching theory [8], we present a distributed approach that finds a suboptimal solution without any third party rule-enforcing authority.

III. Hierarchical Matching Game

The matching between UE and MVNO is performed in the low-level while matching between MVNO and InP is at high-level. Specifically, in the high-level, the InP, acts as the vendor and the MVNOs act as the buyer. In the low-level, each MVNO plays the vendor role and the UEs act as the buyers. It is assumed that each buyer can be associated to only one vendor. However, a vendor can accommodate multiple buyers. Thus, our design corresponds to a *many-to-one matching* [8] given by the tuple $(B, V, q_\upsilon, \succ_B, \succ_V)$. Here, $\succ_B \triangleq \{\succ_b\}_{b \in B}$ and $\succ_V \triangleq \{\succ_\upsilon\}_{\upsilon \in V}$ represent the set of the preference relations of the buyers B and vendors V, respectively.

Definition 1: A matching μ *is defined by a function from the set* $B \cup V$ *into the set of elements of* $B \cup V$ *such that: (i)* $|\mu(b)| \leq 1$ *and* $\mu(b) \in V$, *(ii)* $|\mu(\upsilon)| \leq q_\upsilon$ *and* $\mu(\upsilon) \in 2^{|B|} \cup \phi$, *where* q_υ *is the quota of* υ, *and (iii)* $\mu(b) = \upsilon$ *if and only if* b *is in* $\mu(\upsilon)$.

A. Low-Level matching Game Between MVNO and UE

UEs and MVNOs form the two sides of the matching game. However, in our model, each MVNO m can buy resources from multiple InPs. Therefore, inspired by the works in [11], for each MVNO m, we create n dummies ($n \in N$ that represents the InP-BS), where each dummy MVNO [2] is represented by m_n. Then, the matching is performed on the basis of preference profiles of UEs and these MVNOs, denoted by $\mathcal{P}_k$ and $\mathcal{P}_{m_n}^{l}$ (MVNO in low-level game).

Then, from (2), a UE k ranks a MVNO m_n [3] based on its offered price in an non-decreasing order given by:

$$U_k(m_n) = \beta_{m_n}^M, \quad \forall m_n. \quad (10)$$

Through (4), a MVNO m ranks all UEs based on the profit they yield in a non-increasing order by:

$$U_{m_n}(k) = \max(\beta_{m_n}^M d_k - \beta_n^I l_{k,n}, 0), \quad \forall k. \quad (11)$$

Note that, the value of d_k and $g_{n,k}^c$ of UE k are sent to the MVNO m_n. To evaluate (11), MVNO m_n calculates the required channels (i.e., $l_{k,n}$) for a UE k and ranks them based on the profit they yield in $\mathcal{P}_{m_n}^{l}$. Moreover, here, a UE k is assumed to be indifferent towards all the channels provided by a single InP-BS n because of homogeneous channel gain values while they can be different for different InP-BSs. Furthermore, if the revenue from a UE k is negative, that UE is not ranked in $\mathcal{P}_{m_n}^{l}$. However from (6), each MVNO can only serve limited UEs, i.e., q_{m_n} [4] which is upper bounded by

[2] In the remainder of this paper, we omit the term dummy without confusion.

[3] A MVNO m with n dummies have same price, thus, all UEs have same ranking for these n dummies. By random selection, we achieve strict ranking among these dummy MVNOs m_n.

[4] q_{m_n} represents the available channels of InP-BS n.

the slice provided to it by the InP. Then, the goal is service selection of each UE k to a MVNO m_n via matching.

B. High-Level Matching Game Between MVNO and InP

Next, each MVNO (i.e., dummy MVNO) require a slice from a specific InP to serve the UEs matched to it (i.e., $\mu(m_n)$). We denote the demand of each MVNO as $d_{m_n} = \sum_{k\in\mu(m_n)} d_k$. Now both MVNOs and InPs define their respective preference profiles as $\mathcal{P}^u_{m_n}$ and $\mathcal{P}_n$. Then, each MVNO targets to reduce its cost. Therefore from (4), MVNO m ranks InPs based on their price in an non-decreasing order as:

$$U_{m_n}(n) = \beta^I_n, \quad \forall n. \tag{12}$$

Through (7), the InPs maximize its revenue by selling its slices while achieving fairness among UEs. Therefore, it ranks the buyers in a non-increasing manner:

$$U_n(m_n) = \sum\nolimits_{k\in\mu(m_n)} \log(R^{s_n}_{n,k}) + \omega\beta^I_n\gamma_{m_n}, \quad \forall m_n. \tag{13}$$

Here, assume that the values of d_{m_n} and the set of UEs that are matched in the low-level stage (i.e., $k \in \mu(m_i)$) are sent to the InPs in the proposal phase. Then, InP calculates the required slice size, i.e., γ_{m_n} to fulfill MVNO's m_n demand. This information is required by the InP to rank a MVNO m_n through (13).

Algorithm 1 Hierarchal Matching Algorithm (HM)

1: **initialize**: $\tau = 0, \mathcal{G}^\tau_n = 0, \forall n$.
2: **while** $\mathcal{G}^\tau_n \neq \mathcal{G}^{\tau+1}_n$ **do**
3: $\quad \tau = \tau + 1$.
Stage 1: Low-Level Matching - Service Selection:
4: $\quad$ **input**: $t = 0, q^{(0)}_{m_n} = q^\tau_{m_n}, \mathcal{P}_k{}^{(0)} = \mathcal{P}_k, \mathcal{P}_{m_n}{}^{(0)} = \mathcal{P}^l_{m_n}, \forall m_n, k \notin \mathcal{G}^\tau_n$.
5: $\quad t \leftarrow t+1, \forall k \in \mathcal{K}$, propose to m_n according to $\mathcal{P}_k{}^{(t)}$.
6: $\quad$ **while** $k \notin \mu(m_n)^{(t)}$ and $\mathcal{P}^{(t)}_k \neq \emptyset$ **do**
7: $\quad\quad$ **if** $q^{(t)}_{m_n} \leq l_{k,n}$ **then**
8: $\quad\quad\quad \mathcal{P}'^{(t)}_{m_n} = \{k' \in \mu(m_n)^{(t)} | k \succ_{m_n} k'\} \cup \{k\}$.
9: $\quad\quad\quad k'_{lp} \leftarrow$ the least preferred $k' \in \mathcal{P}'^{(t)}_{m_n}$.
10: $\quad\quad\quad$ **while** $(\mathcal{P}'^{(t)}_{m_n} \neq \emptyset) \cup (q^{(t)}_{m_n} \geq l_{k,n})$ **do**
11: $\quad\quad\quad\quad \mu(m_n)^{(t)} \leftarrow \mu(m_n)^{(t)} \setminus k'_{lp}, \quad \mathcal{P}'^{(t)}_{m_n} \leftarrow \mathcal{P}'^{(t)}_{m_n} \setminus k'_{lp}$.
12: $\quad\quad\quad\quad q^{(t)}_{m_n} \leftarrow q^{(t)}_{m_n} + l_{k'_{lp},n}, \quad k'_{lp} \leftarrow k' \in \mathcal{P}'_{m_n}{}^{(t)}$.
13: $\quad\quad\quad$ Remove rejected players from $\mathcal{P}_k{}^{(t)}$ and $\mathcal{P}_{m_n}{}^{(t)}$.
14: $\quad\quad$ **else**
15: $\quad\quad\quad \mu(m_n)^{(t)} \leftarrow \mu(m_n)^{(t)} \cup \{k\}, \quad q_{m_n}{}^{(t)} \leftarrow q_{m_n}{}^{(t)} - l_{k,n}$.
16: $\quad \tilde{X} \leftarrow \mu^*$
Stage 2: High-Level Matching- Resource Purchasing:
17: $\quad$ **input**: $t = 0, q^{(0)}_n = q^\tau_n, \mathcal{P}_{m_n}{}^{(0)} = \mathcal{P}^u_{m_n}, \mathcal{P}_n{}^{(0)} = \mathcal{P}_n, \forall m_n, n$.
18: $\quad t \leftarrow t+1, \forall m_n$, propose to n according to $\mathcal{P}_{m_n}{}^{(t)}$.
19: $\quad$ **while** $m_n \notin \mu(n)^{(t)}$ and $\mathcal{P}^{(t)}_{m_n} \neq \emptyset$ **do**
20: $\quad\quad$ **if** $q^{(t)}_n \leq |\gamma_{m_n}|$ **then**
21: $\quad\quad\quad \mathcal{P}'^{(t)}_n = \{m_n{}' \in \mu(n)^{(t)} | m_n \succ_n m_n{}'\} \cup \{m_n\}$.
22: $\quad\quad\quad m_n{}'_{lp} \leftarrow$ the least preferred $m_n{}' \in \mathcal{P}'^{(t)}_n$.
23: $\quad\quad\quad$ **while** $(\mathcal{P}'^{(t)}_n \neq \emptyset) \cup (q^{(t)}_n \geq |\gamma_{m_n}|)$ **do**
24: $\quad\quad\quad\quad \mu(n)^{(t)} \leftarrow \mu(n)^{(t)} \setminus m_n{}', \quad \mathcal{P}'^{(t)}_n \leftarrow \mathcal{P}'^{(t)}_n \setminus m_n{}'_{lp}$.
25: $\quad\quad\quad\quad q^{(t)}_n \leftarrow q^{(t)}_n + |\gamma_{m_n{}'_{lp}}|, \quad m_n{}'_{lp} \leftarrow m_n{}' \in \mathcal{P}'^{(t)}_n$.
26: $\quad\quad\quad$ Remove rejected players from $\mathcal{P}_{m_n}{}^{(t)}$ and $\mathcal{P}_n{}^{(t)}$.
27: $\quad\quad$ **else**
28: $\quad\quad\quad \mu(n)^{(t)} \leftarrow \mu(n)^{(t)} \cup \{m_n\}, \quad q_n{}^{(t)} \leftarrow q_n{}^{(t)} - |\gamma_{m_n}|$.
29: $\quad \boldsymbol{Y} \leftarrow \mu^*$
30: $\quad$ Update $\mathcal{G}^\tau_n, \forall n$.
31: **output**: Convergence to group stable $\mathcal{G}_n, \forall n$.

C. Hierarchical Matching Algorithm

For the two-sided hierarchical matching game, our goal is to seek a stable matching, which is a key solution concept [8], [10]. Traditional deferred-acceptance algorithm [10] can not be employed as our formulated game involves a *hierarchal* structure and *heterogeneous demands* of buyers. Due to heterogeneous demands, a vendor allows variable numbers of buyers until its quota constraint is not violated [12]. Therefore, formally the blocking pair for this game is defined as:

Definition 2: A matching μ is stable *if there exists no blocking pair $(A', \upsilon) \in 2^{|B|} \cup V$ with $A' \neq \phi$, such that, $\upsilon \succ_b \mu(b)$, $\forall b \in A'$ and $(A \cup A') \succ_\upsilon \mu(\upsilon)$, $A \subseteq \mu(\upsilon)$, where $\mu(b)$ and $\mu(\upsilon)$ represent, respectively, the current matched partners of vendors and buyers.*

Definition 2 states that a pair (A', υ) blocks a matching μ, if vendor υ is willing to accept the buyers in A', and all buyers $b \in B$ prefer υ. A stable solution ensures that no matched vendor υ would benefit from deviating from their current assigned buyers. To tackle this challenge, we propose a novel stable matching algorithm in Alg. 1 that has two stages namely, the *Low-Level Matching- Service Selection* stage and the *High-Level Matching- Resource Purchasing* stage. However, Definition 2 is not enough for stating the stability as our game also involves a *hierarchal* structure. In hierarchical games, a change in player's strategy at a low-level will cause changes in strategy set of players at higher level and, thus, the convergence cannot be achieved until the strategy set of players at low-level is fixed [9]. We address this challenge by creating a group $\mathcal{G}_n$ for each InP n which is formed as a result of both low-level (i.e., $\mu(m_n)$) and high-level (i.e., $\mu(n)$) stages. Formally, we define the group stability as:

Definition 3: The group $\mathcal{G}_n, \forall n \in N$ is said to be stable if it is not blocked by any group $\mathcal{G}'_n$ which is represented by two conditions: i) No UE k outside the group $\mathcal{G}_n$ can join it. ii) No UE k inside the group $\mathcal{G}_n$ can leave it.

After initialization (line 1), all UEs that do not belong to any group $\mathcal{G}^\tau_n$ join the low-level stage and build the preference profiles for iteration τ. Then, a UE k proposes to its most preferred m_n (lines 5-6). i) If m_n quota is full, then, it finds all lower ranked k' than k i.e., $\mathcal{P}'^{(t)}_{m_n}$ which are sequentially rejected until k can be admitted (lines 7-12). If quota is still insufficient, reject k as well. All rejected players then update there respective profiles by deleting the rejected players (line 13). ii) Otherwise, k is accepted and the MVNO m_n updates its quota (lines 14-15). This process is carried out iteratively until convergence, i.e., the outcome of two consecutive iterations t remains unchanged [10]. The output μ^* can be transformed to a feasible service selection vector $\tilde{\boldsymbol{X}}$. Then, MVNOs and InPs build their respective preference profiles based on the output of low-level matching. The same iterative accept-reject procedure (lines 17-29) is applied to find a stable matching μ^* which can be transformed to a feasible resource purchasing vector between MVNOs and InPs, i.e., $\boldsymbol{Y}$. On completion of this stage, each InP n, then updates its group $\mathcal{G}_n = \{(k, m_n) | k \in \mu(m_n), m_n \in \mu(n), \forall k, m_n\}$ which constitutes the accepted UEs and MVNOs at both stages (line 30). Then the rejected buyers, i.e., UE k in low-level and MVNO m_n (consists of UEs that were accepted in low-level by m_n) will enter into the next iteration $\tau + 1$ as new UEs. Both stages will be executed again with updated values of quotas. Alg. 1 terminates once the groups $G_n, \forall n$ do not change for two consecutive iterations (line 31). This represents that there is no further requests that can be fulfilled.

Theorem 1: Each stage of Alg. 1 achieves a stable matching.

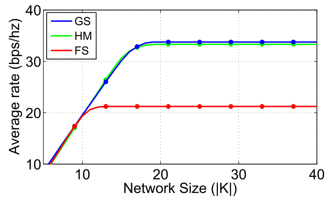

Fig. 2. Average sum-rate of HM, GS, and FS schemes.

Proof: The proof is similar to the one provided in [12]. □

Theorem 2: Alg. 1 converges to a group stable output $\mathcal{G}_n, \forall n \in N$.

Proof: The proof is omitted here for brevity. □

IV. Simulation Results

To simulate we use standard parameters that follow the system guidelines given in [13]. Moreover, we consider a network with 5 MVNOs that rent slices from N InP-BSs to serve randomly located K UEs inside the coverage area of 1000×1000 m. Each InP owns a band of 1.4 MHz (i.e., 6 channels or resource blocks). Moreover, the bandwidth W of each channel and weight parameter ω are set to a normalized value of 1. Each UE k has a demand which is uniformly distributed in the range of $d_k = \{1 \sim 3\}$ bps/hz. The prices for MVNOs and InPs are also uniformly distributed in the range of $\beta_m^M = \{4 \sim 8\}$ and $\beta_n^I = \{2 \sim 4\}$ monetary units/bps/hz, respectively. For comparison purposes, we compare with a fixed sharing scheme (FS), where each MVNO reserves equal number of the channels and a general sharing scheme (GS) in which the MVNOs are not involved and the InP directly performs a single-level matching (in line with [3] and [4]).

In Fig. 2, the average sum-rate versus the network size, (i.e., number of UEs) is shown for the different schemes. The sum-rate increases with network size, which, however, saturates as the network size becomes sufficiently large due to limited bandwidth. Moreover, the sum-rate obtained by HM and GS schemes result in an indistinguishable performance. Specifically, the HM scheme can achieve up to 97% of the average sum rate obtained by the GS scheme, for a large network size (i.e., $|K| > 20$). Additionally, a performance benefit up to 32% can be achieved when compared to the FS approach for $|K| > 15$. Next, in Fig. 3, the average sum-rate is shown with varying number of InP-BS. The average sum-rate increases both with network size and InP-BS density due to additional availability of channels in the network. In Fig. 4, the average sum-rate of HM scheme increases with network size for varying each InP-BS bandwidth from 1.4 to 20 MHz (i.e., $6 - 100$ channels). Finally, a comparison of average iterations of HM scheme under different network sizes with varying InP-BS bandwidth is shown in Fig. 5. The HM scheme achieves convergence under all scenarios in few iterations. However, the iterations increase with the network size because of the increasing number of UE's proposal and accept-reject procedure of HM. Moreover at higher bandwidth values, there are sufficient channels to meet the demands and thus less iterations are required.

V. Conclusion

We proposed a hierarchical matching algorithm for service selection and resource purchasing in wireless network virtualization. Results have shown that the proposed hierarchical matching algorithm converges in a reasonable amount of time, outperforms the fixed sharing algorithm and achieves a comparable performance to a general sharing approach in terms of average sum-rate. As a future extension, we intend to include dynamic pricing and study its impact on the system's performance.

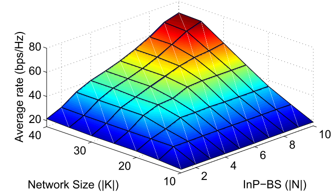

Fig. 3. Average sum-rate for varying InP-BS density.

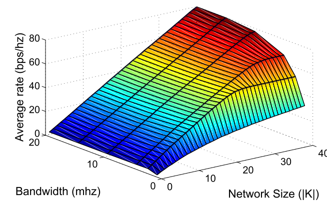

Fig. 4. Average sum-rate for varying InP-BS bandwidth.

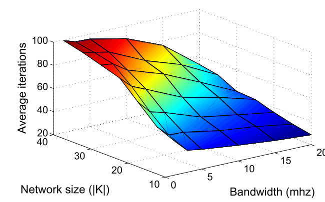

Fig. 5. Average iteration for varying InP-BS bandwidth.

References

[1] C. Liang *et al.*, "Wireless network virtualization: A survey, some research issues and challenges," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 358–380, 1st Quart., 2015.

[2] C. Liang *et al.*, "Distributed resource allocation in virtualized wireless cellular networks based on ADMM," in *Proc. IEEE Conf. Comput. Commun. Workshops (INFOCOM)*, Apr. 2015, pp. 360–365.

[3] S. Parsaeefard *et al.*, "Joint user-association and resource-allocation in virtualized wireless networks," *IEEE Access*, vol. 4, pp. 2738–2750, Apr. 2016.

[4] R. Dawadi *et al.*, "Energy-efficient resource allocation in multi-cell virtualized wireless networks," in *Proc. IEEE Int. Conf. Ubiquitous Wireless Broadband (ICUWB)*, Montreal, QC, Canada, Oct. 2015, pp. 1–5.

[5] K. Zhu *et al.*, "Virtualization of 5G cellular networks as a hierarchical combinatorial auction," *IEEE Trans. Mobile Comput.*, vol. 15, no. 10, pp. 2640–2654, Oct. 2016.

[6] S. Boyd and L. Vandenberhe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

[7] F. P. Kelly *et al.*, "Rate control for communication networks: Shadow prices, proportional fairness and stability," *J. Oper. Res. Soc.*, vol. 49, no. 3, pp. 237–252, Mar. 1998.

[8] Y. Gu *et al.*, "Matching theory for future wireless networks: Fundamentals and applications," *IEEE Commun. Mag.*, vol. 53, no. 5, pp. 52–59, May 2015.

[9] K. Hausken *et al.*, "Formalization of multi-level games," *Int. Game Theory Rev.*, vol. 6, no. 2, pp. 195–221, 2004.

[10] S. M. A. Kazmi *et al.*, "Resource management in dense heterogeneous networks," in *Proc. 17th Asia-Pacific Netw. Oper. Manage. Symp. (APNOMS)*, Busan, South Korea, Aug. 2015, pp. 440–443.

[11] Y. Chen *et al.*, "TAMES: A truthful double auction for multi-demand heterogeneous spectrums," *IEEE Trans. Parallel Distrib. Syst.*, vol. 25, no. 11, pp. 3012–3024, Nov. 2014.

[12] S. M. A. Kazmi *et al.*, "Optimized resource management in heterogeneous wireless networks," *IEEE Commun. Lett.*, vol. 20, no. 7, pp. 1397–1400, Jul. 2016.

[13] 3GPP, "Evolved universal terrestrial radio access (E-UTRA): Physical layer procedures, Release 11," Eur. Telecommun. Standards Inst., Tech. Rep. 3GPP TS 36.213, version 11.1.0, Dec. 2012.