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 paper, we study the service selection and resource purchasing problem for a virtualized network. We model this problem as a two-stage combinatorial optimization problem. To solve this problem, we propose a hierarchical matching game based scheme which enables distributed implementation while satisfying the requirements of efficient resource allocation and strict isolation. Simulation results show that the proposed hierarchical matching algorithm 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 while converging in a reasonable amount of time.**

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

I. Introduction

Wireless Network Virtualization (WNV) is a promising candidate to support the deluge of cellular traffic for the forthcoming fifth generation (5G) networks [1]. In a WNV, infrastructure providers (InPs) provide their physical resources as a service to the mobile virtual network operators (MVNOs) to serve its users. The physical resources (i.e., spectrum, power, backhaul/fronthaul, and antennas) of an InP are abstracted into isolated virtual resources (i.e., slices) which are then transparently shared among different MVNOs. Efficient allocation of physical resources to end users have received significant attention in a single-cell WNV scenario [2]. 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. Then, a significant challenge pertaining to such a scenario is the efficient allocation of the resources such that the total performance of WNV over a specific region is improved. Moreover, traditional resource allocation approaches based on single-cell WNV do not directly apply to multi-cell WNV.

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], [4] in which the authors investigate the resource allocation problem in a multi-cell based WNV. They applied successive convex approximation (SCA) and complementary geometric programming (CGP) to propose an iterative algorithm for solving the non-convex optimization problem. 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. Through intra-resource customization, MVNOs can individually decide how the resources within the slice can be allocated. The works in [5] consider the latter approach for resource allocation that has shown improved user satisfaction, social efficiency and resource utilization. By employing such an approach, the resource allocation problem in WNV becomes a hierarchical (i.e., two-level) problem for which they propose a two-level hierarchical auction scheme. 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 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. Inspired by [5], this work also consider a two-level resource allocation problem following the latter approach for resource allocation in WNV. 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 because now InP is only responsible for allocating resources to each MVNO compared to existing works [3], [4] where the resource allocation has to be obtained directly for all users. 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. Moreover, the problem considers both the revenue maximization for the InPs and MVNOs while guaranteeing MVNOs service contract agreements.
- To solve this problem, we develop a hierarchal matching algorithm that achieves a near optimal solution and enable distributed implementation with affordable computational complexity.
- Simulation results show that the proposed hierarchical algorithm achieves a stable allocation and outperforms the fixed sharing approach by 32% and achieves up to 97% of average sum rate obtained by the optimal approach (general sharing scheme).

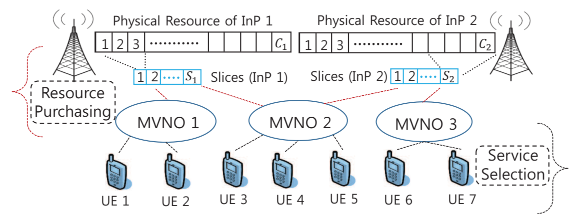

Figure 1: System model: The InP owns the physical resources, virtualizes them into slices and allocates to multiple MVNOs.

II. System Model and Problem Definition

Consider a downlink of a cellular network consisting a set of N base stations (BSs), each representing a cell which is owned by an InP. [1] The InP provides its virtual network service to a set of M mobile virtual network operators (MVNOs) by individual contracts. Moreover, a MVNO $m \in M$ provides its service to a set K_m of subscribed 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. Fig. 1 illustrates our system model.

A. Channel Model and Assumptions

Each InP owns a set of C_n orthogonal channels, each with bandwidth W. We consider a system with static inter-InP interference such that the interference from other InPs is absorbed into the background

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

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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. Moreover, 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 k on a slice s_n of an InP n is:

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

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

The goal in WNV is to maximize the objectives of all UEs, MVNOs and InPs. Each UE $k \in K$ chooses its service as follows:

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

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

where $x_{k,m} \in \boldsymbol{X}$ is the binary 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 represents the demand of the UE k, and β_m^M represents the per unit price of MVNO m. Minimizing (2) achieves the UE's goal to pay the minimum for its demand 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 by determining the required channels with the least cost and optimizing its bandwidth according to the slice price offered by the InP. Then, the MVNO m problem is given as:

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

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

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

where $\tilde{x}_{k,m} \in \tilde{\boldsymbol{X}}$ is the binary service selection 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 binary 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 by InP n.

Finally, the InP aims to satisfy the demands of MVNOs such that the contracts agreements are not violated by solving the following:

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

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

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

where $y_{m,n}^{s_n} \in \boldsymbol{Y}$ is the binary resource purchasing 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. One of the fundamental requirements of WNV is the isolation among different MVNOs which is achieved by guaranteeing certain predetermined requirements or contract service agreement (e.g., minimum share of resource or data rate) by the InP. We consider isolation at the physical resource level, i.e., channels [5]. Through (8) we ensure that allocated slices are less than total slices owned by an InP and the constraint in (9) ensures the contract agreement that is considered as an isolation constraint.

Unfortunately, the optimization 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 optimal 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 which has the ability to solve combinatorial problems [8], we present a distributed approach. Our approach consists of two-level matchings that is able to find a suboptimal solution without any third party rule-enforcing authority and achieve lower-complexity.

III. Hierarchical Matching Game

The proposed hierarchical matching game consists of two levels in which matching between UE and MVNO is performed in the low-level while matching between MVNO and InP is at high-level. Both matching problems can be formulated as a two-sided matching game. Specifically, in the high-level, the InP, who owns the physical resources, 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 $(B, V, q_v, \succ_B, \succ_V)$. Here, $\succ_B \triangleq \{\succ_b\}_{b \in B}$ and $\succ_V \triangleq \{\succ_v\}_{v \in V}$ 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) $|\mu(v)| \leq q_v$ and $\mu(v) \in 2^{|B|} \cup \phi$, where q_v is the quota of v, and (iii) $\mu(b) = v$ if and only if b is in $\mu(v)$.*

A. Low-level matching game between MVNO and UE

In the low-level, 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), to rank potential matchings based on the local information. Then, from (2), a UE k ranks a MVNO m_n [3] based on its offered price in an non-decreasing order given by the following preference function:

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

Similarly, from (4), a MVNO m ranks all UEs based on the profit they yield in a non-increasing order in its preference profile. Therefore, we have,

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

Note that, the value of d_k and $g_{n,k}^c$ of UE k are sent to the MVNO m_n. Then 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 its preference profile $\mathcal{P}_{m_n}^l$. 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 (i.e., the channel gains values of different channels owned by an InP-BS are the same for a UE k, 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 $\mathcal{P}_{m_n}^l$ by the MVNO. However from (6), each MVNO can only serve limited UEs, i.e., q_{m_n} [4] which is upper bounded by 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.

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

[3] As the price of a MVNO m with n dummies will be same, the UEs will have the same ranking for these dummy MVNOs m_n. To achieve strict ranking for these m_n MVNOs, simply break the tie among these dummy MVNOs m_n by random selection.

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

Algorithm 1 Hierarchal Matching Algorithm (HM)

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

B. High-level matching game between MVNO and InP

Once a solution to the low-level matching game is obtained, we can solve the high-level game. Here each MVNO (i.e., dummy MVNO) require a slice from a specific InP to serve the UEs matched to it in the low-level stage (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 $\mathcal{P}^u_{m_n}$ (MVNO in high-level game) and $\mathcal{P}_n$. Once low-level game is solved, then a MVNO targets to reduce its cost to obtain slices. Therefore from (4), MVNO m ranks InPs based on their price in an non-decreasing order as:

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

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

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

Here, we 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). Once this information is acquired, each InP can rank all the MVNOs.

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 in matching theory [8], [10]. To find a stable matching, the deferred-acceptance algorithm can be employed [10]. However, 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]. These aforementioned challenges prevent the use of standard deferred-acceptance algorithm. Therefore, we formally define the blocking pair for the formulated game as follows:

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

Definition 2 is based on the following intuition, a pair (A', v) blocks a matching μ, if vendor v is willing to accept the buyers in A', possibly after rejecting some of its current buyers in $\mu(v)$, i.e., $A \subseteq \mu(v)$ and all buyers $b \in B$ prefer v over their current match $\mu(b)$. In our game, a stable solution ensures that no matched vendor v would benefit from deviating from their assigned buyers b with a new buyer b'. To tackle this challenge, we propose a novel stable matching algorithm in Alg. 1. The algorithm 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 for our proposal as our game 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. Therefore, to find a stable solution, we have to guarantee that no change in players' strategy occurs at the low-level once convergence is achieved [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. Finally we prove that Alg. 1 converges to a group stable allocation. 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 the following 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 $\mathcal{G}_n^{\tau}$ join the low-level stage and build the preference profiles for iteration τ. Then, each unassigned UE k proposes to its most preferred MVNO m_n according to $\mathcal{P}_k$ (lines 5-6). i) If MVNO m_n quota is full, then, it finds the current matched UEs k' that ranks lower than k in its preference profile i.e., ${\mathcal{P}'}_{m_n}^{(t)}$. Each least preferred UE $k'_{lp} \in {\mathcal{P}'_{m_n}}^{(t)}$ is then sequentially rejected until k can be admitted or there is no additional k' to reject (lines 7-12). If MVNO m_n still has insufficient quota to admit k, then k is also rejected. All rejected UEs and MVNOs then update there respective preference 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 either all the UEs are assigned to MVNOs or there are no more MVNOs to propose. This stage terminates when the outcome of two consecutive stage iterations t remains unchanged [10]. The output of this stage μ^* can be transformed to a feasible service selection vector $\tilde{\boldsymbol{X}}$. After the low level matching, MVNOs and InPs build their respective preference profiles based on the output of low-level matching. Similar to the low-level matching, 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). Furthermore, the rejected buyers in both stages, 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. Then, both these stages will be executed again with updated values of remaining InP and MVNO quotas. The algorithm 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 from UEs or there exists not enough InP-BS resources to fulfill UEs request.

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

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

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

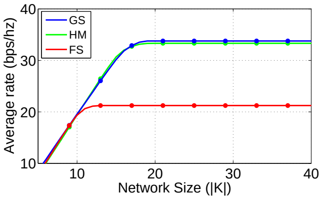

Figure 2: Average sum-rate of HM, GS, and FS schemes.

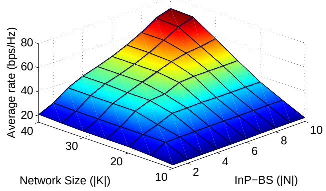

Figure 3: Average sum-rate vs. network size for varying InP-BS density.

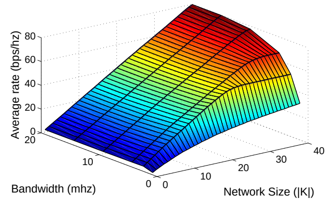

Figure 4: Average sum-rate vs. network size for varying InP-BS bandwidth.

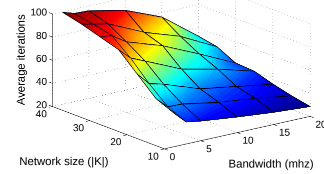

Figure 5: Average iteration vs. network size for varying InP-BS bandwidth.

Proof. The proof is omitted here for brevity. □

IV. Simulation Results

To simulate our proposal we consider the standard parameters of cellular technologies that follow the system guidelines given in [13]. Moreover, 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. In our simulation, each UE k has a demand which is uniformly distributed in the range of $d_k = \{1 \sim 3\}$ bps/hz. Note that in this work we do not differentiate between the priority of user demands and assume all users' demand have homogeneous priority. We set the prices for MVNOs and InPs that is 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. Furthermore, all results are obtained by averaging over a large number of independent simulation runs, each of which realizes random traffic demands, pricing, locations of InP-BSs, UEs, and channel power gains. For comparison purposes, we compare the proposed algorithms with two baseline schemes [5]. First, a fixed sharing scheme (FS), where each MVNO reserves equal number of the channels. This fixed sharing can also be viewed as the case in which there is no wireless virtualization and a comparison of the proposal with FS scheme reflects the benefits achieved by WNV over the traditional cellular networks. Second, a general sharing scheme (GS) in which the MVNOs are not involved and the InP directly performs a single-level matching for the channel allocation, which is in line with some existing works such as [3], [4].

In Fig. 2, the average sum-rate versus the network size, (i.e., number of UEs) is shown for the different schemes. It is observed that the sum-rate increases with network size, which, however, saturates as the network size becomes sufficiently large. This is due to the limited network bandwidth for each InP (i.e., 1.4 MHz). We also observe that 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., $|K| > 20$). Thus, it can be inferred that the HM scheme is close to optimal. Moreover, 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 vs network size is shown with varying number of InP-BS for the HM scheme. We observe that the average sum-rate increases when both the network size and InP-BS density increase. This is due to additional availability and allocation of channels in the servicing area. Similarly, 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). Furthermore, we observe that when the operating InP-BS bandwidth is higher than 15 MHz (i.e., 75 channels per InP-BS), the sum-rate saturates and does not increase as the network has enough resources to fulfill all network sizes demands. 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, we also infer that as the InP-BS bandwidth is increased from 1.4 MHz to 20 MHz, the average iterations decrease. This can be explained as bandwidth increases, there are sufficient channels to meet the demands. Therefore, less iterations are required to converge to a stable group as most of the proposals are accepted by the sellers due to large available quota (i.e., channels).

V. Conclusion

In this paper, we proposed a hierarchical matching algorithm for service selection and resource purchasing in wireless network virtualization. Distributed implementation of the proposed algorithm has also been discussed in detail. Numerical studies have shown that the proposed hierarchical matching algorithm converges in a reasonable amount of time. Moreover it 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.

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