# A Matching Game Approach for Resource Allocation in Wireless Network Virtualization

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## ABSTRACT

Wireless network virtualization is an effective and economical solution that can significantly enhance the performance of existing radio access networks by decoupling of physical infrastructure from the services it provides. This enables sharing the resources (e.g., subchannels, power, and antennas) of physical infrastructure among multiple network operators. However, the infrastructure provider is required to employ an efficient resource allocation technique to dynamically allocate the resources for the users associated with different network operators. Service contracts with different network operators are crucial for the success of the virtulization scheme deployed by the infrastructure provider. In this paper, a matching game based solution is proposed for resource allocation in OFDMA virtualized wireless network. We considers a market model consisting of an infrastructure provider and multiple network operators. The matching based solution takes into account the objectives of both the infrastructure provider and the network operators. The infrastructure provider aims at maximizing its revenue and while the network operators wants to serve their users at the best performance while paying the minimum amount. Furthermore, we prove that the proposal achieves a pareto optimal solution from the infrastructure provider point of view. Simulation results illustrates the effectiveness of our proposal in terms of spectrum efficiency, quality of service and convergence.

## CCS Concepts

•**Networks** → *Wireless access networks;* •**Social and professional topics** → Pricing and resource allocation;

## Keywords

resource allocation, wireless network virtualization, game theory, cellular networks.

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## 1. INTRODUCTION

To meet the demands of the forthcoming fifth generation (5G) cellular networks which are expected to provide higher data rate, lower end-to-end latency, improve spectrum/energy efficiency, and reduced cost, one effective technology is network virtualization [1–3]. Virtualization played a vital role in the data center industry by enabling abstraction and sharing of resources among different parties. Virtualization enables the reduction of the overall equipment cost, easy management and decoupled functionalities. In this paper, we focus on the issue of wireless virtualization and benefits it can yield. In wireless network virtualization, the main goal is to enable resource sharing and to decouple the infrastructure from the service it provides [1, 2].

In the existing cellular systems, the roles of both infrastructure provider (InP) and network operator are tightly coupled with each other and depends upon the underlying physical infrastructure [3]. With wireless network virtualization, the role of infrastructure provider (InP) can be logically separated from the role of network operator. The InP can provide the infrastructure as a service to an virtual network operators (VNOs) and the virtual network operators can further rent their services to a number of users. The services that can be provided by base station (BS) owned by an InP are abstracted into isolated virtual resources (i.e., slices) which are then transparently shared among different VNOs. Specifically, the physical resources (e.g., infrastructure, spectrum, power, backhaul/fronthaul, and antennas) of a BS can be provided as a service and each VNO can virtually own the entire BS [1, 2]. However, reaping the benefits of wireless network virtualization requires meeting significant challenges in terms of resource allocation.

The main challenge in resource allocation for wireless network virtualization is the decision on allocation of the physical resources for VNOs such that it can accommodate the dynamic demands of their users, while satisfying the requirements of efficient resource allocation and isolation among multiple VNOs. Typically, the InP performs the resource allocation, i.e., allocates the physical resources to users of different VNOs according to certain requirements (e.g., predetermined resource sharing ratios).

Resource allocation in wireless network virtualization has attracted significant recent attention [4–9]. The work in [4], formulates the resource allocation strategy for the network as an optimization problem by jointly considering the revenue earned by VNOs by serving end users and the cost of leasing infrastructure from InPs. A distributed virtual

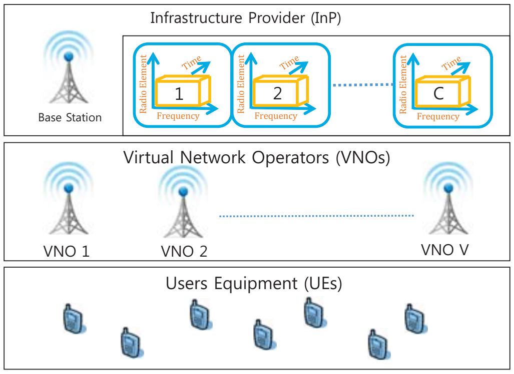


Figure 1: System model: The InP owns the physical infrastructure i.e., BS and subchannels which are virtualized and allocated to multiple VNOs.

resource allocation solution based on alternating direction method of multipliers (ADMM) was proposed to solve this joint problem. An efficient and fast centralized heuristic solution to allocate the radio resource block in multi-cell LTE networks was proposed based on flexible service level agreements of each service provider (SP) in [5]. In [6], a virtual resource allocation scheme for OFDMA based wirless virtualization networks is proposed that can achieve a Pareto optimal allocation based on the market equilibrium price theory. Other notable works for resource allocation can be found in wireless network virtualization can be found in [7–9].

To this end, we design an efficient virtual resource allocation scheme that can overcome the "isolation" hurdle in the wireless network virtualization. Moreover, we take into account the network benefits for the InP and VNOs simultaneously. We employ the concept of matching theory to perform the resource allocation because of its unique ability to characterize the roles of all players, i.e., InP, VNOs, and users. Matching theory is suitable for solving resource allocation problems due to the following reasons: first, interactions among heterogeneous players can be accurately characterized through generally defined preferences; second, the analytical tractability of the solution does not require the objective functions to have special properties such as convexity; last but not least, the matching algorithm can always produce solutions with guaranteed properties such as stability and optimality, etc., and is suitable for online implementation. Additionally, the existing works either considerer the InP's revenue maximization or VNO's cost minimization. Different from the existing works, we consider both the revenue maximization for the InP and cost minimization for VNOs while guaranteeing service contract agreements between the InP and VNOs. Thus, our contribution can be summarized as follows:

- We first formulate the resource allocation problem for the wireless network virtualization as a matching game and design the problem specific preference profile of each player
- Second, we propose a stable one-to-many resource allocation algorithm which can guarantee the isolation constraint. Moreover, we show that the proposed solution is a weak pareto optimal solution for our problem.

The remainder of this paper is organized as follows. In the next section we present the system model and problem formulation Section 3 illustrates in detail, how we map the proposed problem into a matching game and present the proposed allocation algorithm. In Section 4, we present the numerical results to validate the performance of our scheme. Concluding remarks and future extensions are covered in Section 5.

# 2. SYSTEM MODEL

Consider a downlink cellular network with a single base station (BS). The BS and spectrum are managed and owned by an infrastructure provider (InP). In our model, we consider the spectrum as a set $\mathcal{C}$ of orthogonal sub-channels with bandwidth $w$. InP provides services to a set $\mathcal{V}$ of virtual network operators (VNOs) based on some service level agreements (SLA). Moreover, each VNO $v$ enables a set of users represented by $K_v$ which needs its service. The InP creates virtual resource (VR) slices based on the request from VNOs, and operates the VR slices and assigns them to VNOs' subscribed users. In general, the isolation between the slices of different VNOs is required by any wireless virtualization scheme. In our model, we consider, isolation between different VNOs is achieved by guaranteeing certain predetermined requirements or contract agreements between VNO and InP similar to [7]. This allows a dynamic sharing of spectrum between the VNOs.

## 2.1 Virtual Resource Model

In our model, we assume that all transmitters use a slowly changing transmit power (fixed power) over the VR allocation for carrying out their respective transmissions and thus the interference power is also constant over the VR. For VR allocation, we introduce binary variables $x_{v,k}^c$, as follows:

$$x_{v,k}^c = \begin{cases} 1, & \text{if user } k \text{ of VNO } v \text{ is assigned VR } c, \\ 0, & \text{otherwise.} \end{cases}$$

Moreover, we assume that a VR can be assigned to at most one user to guarantee the service contract agreement. Therefore, we have:

$$\sum_{c\in\mathcal{C}} x_{v,k}^c \geq 1, \ \forall k \in K_v, \forall v \in \mathcal{V}. \tag{1}$$

We always set $x_{v,k}^c = 0$ for any VNO's $v$ user $k$, which is not assigned VR $c$. The received SINR pertaining to the transmission of VNO's $v$ user $k$ over $c$ with transmit power $P_v^c$ is:

$$\gamma_{v,k}^c = \frac{P_v^c g_{v,k}^c}{\sum\limits_{l\in\mathcal{V}, l\neq v} P_l^c g_{l,k}^c + \sigma^2}, \tag{2}$$

where $P_l^c$, represent the transmit powers of the VNO $l$, The VR gain between VNO $v$ and its user $k$ is $g_{v,k}^c$ whereas $g_{l,k}^r$ is the VR gain from the VNO $l$ to user $k$ of VNO $v$. Then, the achievable data rate of the user $k$ of VNO $v$ on VR $c$ can be given by the following equation:

$$r_{v,k}^c = x_{v,k}^c W \log(1 + \gamma_{v,k}^c), \tag{3}$$

where $W$ is the bandwidth of VR $c$, unless otherwise stated, we assume $W = 1$ without loss of generality.

## 2.2 Economic Model

The InP owns the physical substrate, i.e., BS and spectrum. It creates VR slices based on the request from VNOs, and assigns them to VNOs' subscribed users. In this work, we also study the affect when players in the system act selfishly which is critical for network virtualization [10]. Moreover, one of the main motivation behind network vitrualization is cost saving factor of the network, i.e., maximization of revenue for InPs and cost minimization for the MVNOs. The business model for the InP is that it sells its owned spectrum and charges a price i.e., $p_c$ (per unit of VR $c$) to the VNO $v$. The goal of the InP lies in maximizing its revenue by setting the right price to satisfy the demand of VNOs while guaranteeing the SLA. Therefore the utility of an InP can be states as follows:

$$U_I(\boldsymbol{x},\boldsymbol{p}) = \sum_{v\in\mathcal{V}} x_v p_v, \tag{4}$$

where $x_v = \sum_{k\in K_v}\sum_{c\in\mathcal{C}} x^c_{v,k}, \forall\mathcal{V}$ represents the total VRs sold to VNO $v$, and $p_v$ is the price paid by VNO $v$ to InP for the using the VRs.

On the contrary, each VNO want to serve their users at the best performance and pay the minimum to InP by optimizing the VR demand according to the VR price offered by the InP. Thus, the utility of a VNO $v$ can be presented as follows:

$$U_v(\boldsymbol{x}) = \sum_{k\in K_v}\sum_{c\in\mathcal{C}} r^c_{v,k} - \sum_{c\in\mathcal{C}} p^c_v \sum_{k\in K_v} x^c_{v,k}. \tag{5}$$

## 2.3 Problem Statement

The goal is to maximize the total utility of the system from the prospective of both InP and VNOs as explained in Section 2.2. Therefore, our objective is to maximize the revenue attained by InP while simultaneously meeting the demands of VNOs. Then, the considered VR allocation problem can be stated as follows:

$$\mathbf{P1}: \underset{(\boldsymbol{p},\boldsymbol{x})}{\text{maximize}}\ U_I(\boldsymbol{x},\boldsymbol{p}) + \sum_{v\in\mathcal{V}} U_v(\boldsymbol{x}) \tag{6}$$

subject to:

$$\sum_{c\in\mathcal{C}} x^c_{v,k} \geq 1,\ \forall k\in K_v, \forall v\in\mathcal{V}, \tag{7}$$

$$r_{v,k} > r^{min}_{v,k}, \forall k\in K_v, \tag{8}$$

$$x^c_{v,k}\in\{0,1\},\ \forall v,k,c, \tag{9}$$

$$p^{\min} \leq p_v \leq p^{\max},\ \forall v\in\mathcal{V}. \tag{10}$$

In **P1**, constraint (7) is to ensure that each VNO user $k$ can be allocated to at most one VR $c$. Constraint (8) represents the contract agreement constraint for all VNO users and it can be considered as isolation provisioning. The binary VR allocation indicator variable is represented by the constraint (9). Finally, (10) represents the pricing constraint. Problem **P1** is a integer linear programming, and finding the solution becomes NP-hard, for a practical size of network. [11,12].

In order to have a low complexity, self-organizing and a distributed solution, we aim that **P1** can be solved in a distributed manner. Therefore, we employ the concept of matching game or matching theory to map problem **P1** into a matching game and then discuss the details of the solution in the following section.

# 3. MATCHING-BASED ALLOCATION

Matching theory is a promising technique that can be applied for VR allocation problem and can overcome the limitations of optimization especially for combinatorial problems [16]. The benefits of matching theory comes from the distributive nature of control in the system. Furthermore, matching theory has an implicit benefit in which players has the ability to define its individual utilities depending upon his local information through which a decentralized and self organizing solution for the VR allocation problem can be achieved. The matching problems can be broadly classified as follows; two sided matching games with two sided preferences, two sided matching games with one sided preferences and one sided matching game with preferences. In this work, we use the two sided matching game with two sided preferences class to solve the proposed VR allocation problem. This technique of matching theory divides the matching players into two distinct disjoint sets and each member of a set ranks a subset of the members of the other set in order of preference. The preference of one set over the other set is derived from the local information available to each member. The VR allocation matching problem is defined as to find a match between VNO's users and VR owned by the InP, given their individual preferences derived from different objectives.

## 3.1 Matching Game Formulation

Matching theory is a mathematical framework that can be used to solve VR allocation problem [**?**,**?**,**?**]. Here, we formulate the VR allocation as a matching game problem, then we define the utility and finally present a low-complexity algorithm that can find a stable matching which is a key concept for a matching game.

We assume each VNO user $k$ forms a set which can use a single VR, to enable constraint (7). However, to use this VR, the SLA for the VNO user should be guaranteed, i.e., constraint (8). Moreover, we consider a VR can be allocated to multiple VNO users guaranteeing the required rate. This allows to achieve a higher spectrum efficiency. The other set is the available VRs which would evaluate each VNO user $k$ and will match to the best user $k$. Therefore, our design corresponds to a *one-to-many matching* given by the tuple $(\mathcal{K},\mathcal{C},\succ_{\mathcal{K}},\succ_{\mathcal{C}})$. Here, $\succ_{\mathcal{K}} \triangleq \{\succ_k\}_{k\in\mathcal{K}}$ and $\succ_{\mathcal{C}} \triangleq \{\succ_c\}_{c\in\mathcal{C}}$ represent the set of the preference relations of the VNO users and VRs, respectively. Formally, we define the matching as follows:

Definition 1. *A matching $\mu$ is defined by a function from the set $\mathcal{K}\cup\mathcal{C}$ into the set of elements of $\mathcal{K}\cup\mathcal{C}$ such that:*

1. $|\mu(k)|\leq 1$ *and* $\mu(k)\in\mathcal{C}$,
2. $|\mu(c)|\leq q_c$ *and* $\mu(c)\in\mathcal{K}\cup\phi$,
3. $\mu(k)=c$ *if and only if* $k$ *is in* $\mu(c)$,

where $\mu(k)=\{c\} \Leftrightarrow \mu(c)=\{k\}$ for $\forall c\in C, \forall k\in K$ and $|\mu(.)|$ denotes the cardinality of matching outcome $\mu(.)$. The first two properties state that the matching is a one-to-many relation in the sense that a VNO user $k$ can be associated with one VR $c$ only and can be shared among different VNO user only if the required SLA is achieved which are the constraints (7) and (8) of problem **P1**. Here, $q_c$ represents the quota of VR $c$ which represents the number of VNO users that can guarantee the SLA agreement by using VR. Additionally, there are also cases when a user $k$ is not feasible to use a VR $c$ due to the violation of constraint (7), and, this case is represented by the following matching i.e., $\mu(c)=\phi$.

### 3.1.1 Preference profiles of Players

The interactions between the InP and VNOs can be characterized as a two-sided matching game model. The InP broadcasts the VR price initially and then the VNOs respond by the VR demands for each users. All VNOs aim to serve their uses at the best performance and aim at paying the minimum to InP. The InP wants to maximize its revenue by setting the right VR price to satisfy the demand of VNOs while guarantees the contracts agreements, i.e., minimum required bandwidth. In order to evaluate each other, players from both sides built a preference profile in order to rank the players of the opposite side. In the proposed VR allocation problem, the two sides i.e., VNO users and VR make their preference profiles by utilizing local information available at each side. The preference profile for the VNO users $k$ is based on the following preference function:

$$U^k(c) = \max\{( \ r^c_{v,k} - r^{min}_{v,k}), 0\} \tag{11}$$

The preference function here represents the goal of an VNO, i.e., serve users at the best performance and pay the minimum to InP by optimizing the VR demand according to the VR price offered by the InP. (11) represents the feasibility condition represented by constraint (8). Note here that if a VR $c$ cannot fulfill the rate requirement of user $k$, then a zero utility is assigned by user $k$ to VR $c$ and is not considered in the ranking. Note that, on each $c$, each VNO $V$ will choose its user $k$ with highest utility $U^v(c) = \max_k U^k(c)$. Moreover, each VNO user $k$ ranks all the VR $c$ in increasing order in its preference profile represented by $\mathcal{P}_k$, i.e., the lower the price of VR, the higher it ranks. Note that, a VR $c \in \mathcal{C}$ which produces a lowest price according to (11) will be preferred over a VR $c' \in \mathcal{C}$ by a user $k$ i.e., $c \succ_k c'$ for carrying out its transmission and would be placed higher in its preference profile. All VRs which are not feasible and have a zero utility will be placed at the end of the preference profiles. Note that here the preference profiles $P_k$ of all users $k$ are managed by their respective VNOs.

Similarly, each VR $c$ also needs to have a preference profile of the VNO users $k \in K_v$ ranked according to its preference function. This preference list for each VR $c$ is formed by the InP provider and represented by $\mathcal{P}_c$. The preference function is given by:

$$U^c(\mathcal{N}) = \max_{k_v}\{|\mathcal{N}_{k_v}| : r^c_{\mathcal{N}_{k_v}} > r^{min}_{\mathcal{N}_{k_v}}\}, \tag{12}$$

where $\mathcal{N} \subseteq \bigcup_{v \in \mathcal{V}} K_v$ represents a set of VNO users $k$ associated to any VNO $v$ that can be given VR $c$ and meet the service agreement of all users in the set $\mathcal{N}$, $r^c_{\mathcal{N}_{k_v}}$ represents the achievable rate for the set of users, and $r^{min}_{\mathcal{N}_{k_v}}$ represents the minimum requirement of all users in the set.

According to (12), each VR $c$ chooses a subset of users $\mathcal{N}$ such that the rate achieved by $\mathcal{N}$ is greater than the minimum required rate of all users in the set. This preference function maximizes the number of elements in $\mathcal{N}$ i.e., maximize the number of users. Note that this allows the InP to generate the maximum revenue (4) while simultaneously meeting the service contracts. The subset with the highest number of elements is the most preferred among all the feasible subsets and ranked accordingly.

The information required to build the preference of each VR at the InP includes the set of users waiting to be assigned VR and their minimum rate requirement. Note that, this requires some signaling. However, signaling is only involved in sending these values once from the VNOs to the InP, which is relatively small and can be conducted over the air [17]. Similarly, the price values are required by the VNOs to build their preferences which are broad casted by the InP in the network. Once the preference profiles are build by both sides, our gaol is to now design a allocation algorithm to assign VRs to users.

**Algorithm 1** Resource Allocation Algorithm

***Phase 1: Initialization***:
**input**: $\mathcal{P}_k$, $\mathcal{P}_c$, $\forall c, k$.
**initialize**: $t = 0$, $\mu^{(t)} \triangleq \{\mu(k)^{(t)}, \mu(c)^{(t)}\}_{k \in \mathcal{K}, c \in \mathcal{C}} = \emptyset$, $\mathcal{L}_c{}^{(t)} = \emptyset$ $\mathcal{P}_k{}^{(0)} = \mathcal{P}_k$, $\mathcal{P}_c{}^{(0)} = \mathcal{P}_c$, $\forall c, k$.
***Phase 2: Matching***:
**repeat**
    $t \leftarrow t + 1$
    **for** $c \in \mathcal{C}$, propose $k$ according to $\mathcal{P}_c{}^{(t)}$ **do**
        **while** $c \notin \mu(k)^{(t)}$ and $\mathcal{P}^{(t)}_c \neq \emptyset$ **do**
            **if** $U^k(c) \geq 0$, **then**
                **if** $c \succ_k \mu(k)^{(t)}$ **then**
                    $\mu(k)^{(t)} \leftarrow \mu(k)^{(t)} \setminus \mu(k)^{(t-1)}$
                    $\mu(k)^{(t)} \leftarrow c$
                    $\mathcal{P}'^{(t)}_c = \{j' \in \mu(k)^{(t-1)} | c \succ_k j'\}$
                **else**
                    $\mathcal{P}''^{(t)}_c = \{c \in \mathcal{C} | \mu(k)^{(t)} \succ_k c\}$
            **else**
                $\mathcal{P}'''^{(t)}_c = \{c \in \mathcal{C} | U^k(c) \leq 0\}$
                $\mathcal{L}_c{}^{(t)} = \{\mathcal{P}'^{(t)}_c\} \cup \{\mathcal{P}''^{(t)}_c\} \cup \{\mathcal{P}'''^{(t)}_c\}$
                **for** $l \in \mathcal{L}_c{}^{(t)}$ **do**
                    $\mathcal{P}_l{}^{(t)} \leftarrow \mathcal{P}_l{}^{(t)} \setminus \{k\}$
                    $\mathcal{P}_k{}^{(t)} \leftarrow \mathcal{P}_k{}^{(t)} \setminus \{l\}$
**until** $\mu^{(t)} = \mu^{(t-1)}$
***Phase 3: Resource Allocation***:
**output**: $\mu^{(t)}$

## 3.2 Resource Allocation Algorithm

In this section, we present the VR allocation algorithm based on the proposed matching game. The aim of this algorithm is to find a stable allocation which is a key solution concept in matching theory [18, 19] and can be defined as follows:

DEFINITION 2. *A matching $\mu$ is stable if there exists no blocking pair $(k, c)$, where $k \in \mathcal{K}, c \in \mathcal{C}$, such that $c \succ_k \mu(k)$ and $k \succ_c \mu(c)$, where $\mu(k)$ and $\mu(c)$ represent, respectively, the current matched partners of $k$ and $c$.*

The output of the algorithm is the allocation vector of VNO users and the pseudo code is given in Algorithm 1. The presented algorithm is guaranteed to converge to a stable allocation as it is a variant of well known "deffered-acceptance algorithm" [18].

The algorithm has three phases namely, *the initialization phase, the matching phase* and the *VR allocation phase*. In the *initialization phase*, local information is attained by both the sides to rank the other side. It starts by each VNOs submitting its demand for each user i.e., $r^{min}_{v,k}$, $\forall K_m, \mathcal{V}$. The InP in response to it broadcasts its available VRs and the corresponding prices for use. Based on this information of VRs $c \in \mathcal{R}$, each VNO user constructs its preference profile $\mathcal{P}_k$. Similarly, the InP has the information of all the VNO users, it then constructs the preference profile $\mathcal{P}_r$ for the

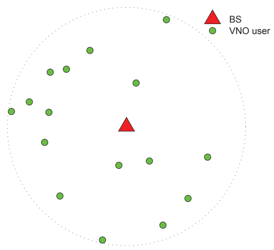


Figure 2: Simulation topology.

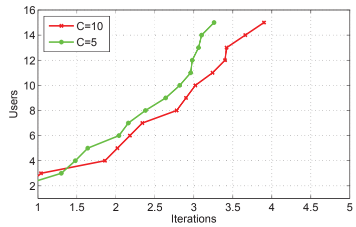


Figure 3: Converge with respect to number of users.

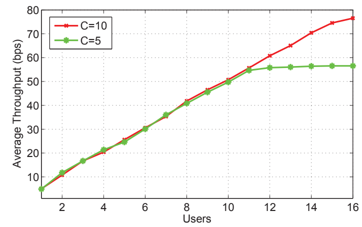


Figure 4: Average throughput vs number of users.

available VR $c$ (Lines 1-3). In the second phase *matching*, each VR $c$ proposes to the best VNO user $k$ according to its preference profile $\mathcal{P}_k$ (Lines 7-8). There are two cases, case 1: If (11) is satisfied, i.e., VNO user $k$ has a positive utility for VR $c$. Then, each VNO user provisionally accept the request from the VR $c$, if its unmatched, i.e., $\mu(k)^{(t)} = \phi$ (lines 9-12). If its matched $\mu(k)^{(t)} \neq \phi$, then it compares the current match with the new proposal and accepts the one which is higher ranked and the lower ranked is rejected (line 13 and 15). As we know that matching $k$ with a higher ranked $c$ will result in a low payment to InP. In case 2, the proposing VR $c$ will be rejected as it does not meet (11). All the rejected VRs will finally added in the rejected list $\mathcal{L}_c{}^{(t)}$ (Line 18). Finally, all the rejected VRs at iteration $t$,i.e., the set $\mathcal{L}_c{}^{(t)}$, is then used by both the sides to update their preference profiles. This means all VR $c$ removes the VNO users $k$ from the $\mathcal{P}_c{}^{(t)}$, and similarly these VNO users also remove $c$ from their respective $\mathcal{P}_k{}^{(t)}$ (lines 20-21). It is to be noted that the matching process is carried out iteratively until a stable match is found between both the sides (line 22). The algorithm will converge when the matching of two consecutive iterations $t$ remains unchanged (line 22). The final stage is the *VR allocation* phase in which the matched VNO users are allowed to transmit on the allocated VRs (lines 23-24).

PROPOSITION 1. *Algorithm. 1 is a variant of well known deferred acceptance algorithm which is guaranteed to converge to a stable point in a limited iterations, as per [18].*

DEFINITION 3. *A matching $\mu$ for VR is weak Pareto optimal if there is no other matching $\mu'$ that can achieve a better utility, where the inequality is component-wise and strict for a pair $(k, c)$.*

THEOREM 1. *Algorithm. 1 produces a weak PO solution for the InP.*

PROOF. Let us consider $\mu$ to be the stable assignment obtained by Alg. 1. Assume $\mu'$ be an arbitrary stable outcome better than $\mu$, i.e., $\mu'$ achieves a higher network data rate. Since the assignment $\mu'$ is better than $\mu$, there exists one VNO user $k'$ assigned to VR $c$ in $\mu'$ whereas in $\mu$ the VR $c$ is matched with VNO user $k$. According to this assumption, VR $c$ prefers VNO user $k'$ compared to $k$, and let $k'$ be assigned to some other VR $c'$ in $\mu$. It is then obvious that $k' \succ_c k$ and $c \succ_{k'} c'$ in the matching $\mu$. Then by Definition 2, $\mu$ is blocked by the pair $(k, c')$ and hence is unstable. This contracts our assumption that $\mu$ is a stable assignment and obtained from Alg. 1. Since there are no stable outcome $\mu'$ which is better than $\mu$, by definition 3, $\mu$ is an optimal assignment. □

# 4. NUMERICAL RESULTS

In this section, we perform simulations under various topologies and scenarios to demonstrates the performance and effectiveness of the resource allocation algorithm. The network topology for our simulations contains a physical BS owned by an InP, with VNO users randomly located inside circles of radius of $r = 500$ m. We consider a network with 3 VNOs each with 5 subscribed user as shown in figure 2. We assume two cases when the InP owns $C = 5$ and 10 OFDMA subchannels, each of which has a total bandwidth of 180 KHz. Moreover, we consider a random but different prices over all subchannels. The noise power is assumed to be $10^{-13}$ W. The small-scale fading coefficients of the BS-to-user links are generated as independent and identically distributed (i.i.d.) Rayleigh random variables with unit variance. The subchannel gain is given by $g_{m,k} = \mathcal{X} d^{-\beta}_{(d_{k,m})}$, where $\mathcal{X}$ function $PL(d_{m,n})$ is a random value generated according to the Rayleigh distribution, $(d_{k,m})$ is the geographical distance between BS and user $k$ of VNO $m$, and $\beta = 3$ is the path-loss component. The VNOs' minimum data rate is assumed to be $r_{min} = 5$ bps/Hz/user. Finally, the maximum BS transmission power is fixed to 43 dBm [17] which is uniformly dived among the available subchannels. Note that, all statistical results stated are averaged over a large number of independent runs of random locations of users and resource gains.

In figure 3, the convergence of Algorithm 1 is shown with respect to number of users in the system. Algorithm 1 converges when both the set of players (i.e., VRs and users) achieve a stable match and do not intend to deviate from their current allocation. Moreover, at convergence the throughput of the system will be saturated. We can infer from the graph that under all scenarios, the proposed resource allocation algorithm converges to a stable allocation after limited number of iterations i.e., less than 4 for both cases when $C = 10$ and 5 with 10 users. Furthermore, note that, for lesser number of VRs in the system, the convergence is achieved earlier. This is because of the fact that, the limited VRs gets saturated and constraint (8) can no longer be maintained if admitted new users by InP. However, due to limited VRs in the system, all users may not be able to get VRs.

Next, in figure 4, the achievable throughput by system is shown with respect to varying number of users in the network. In this simulation, we increased the number of users and observed that the average throughput increases with more users under all scenarios, which, however, saturates as the number of users becomes sufficiently large for the case of $C = 5$ as constraint (8) cannot be maintained for all users. This is because of the limited number of resources available usage of VRs in close proximity users can create interference. Furthermore, for the case when there exists enough VRs in the system, i.e., 10, all users demands are met and the throughput increases. Note that, the revenue of an InP increases as more number of users are allocated VRs. However, there exists a limitation for an InP to abide by the service contracts of VNOs, i.e., isolation constraint if allocating VRs to users which limits it usage.

## 5. CONCLUSION

In this paper, we have proposed a resource allocation algorithms for the VNO users. We used the matching theory to formulate the resource allocation problem and propose a stable, self-organizing and decentralized solution for the proposed problem. Moreover, InP can guarantee the service level agreements between itself and VNOs, if a VR is allocated. We also discuss the distributed implementation of this algorithms in detail. Moreover, we prove the stability and show that the proposed algorithm achieves a pareto optimal solution for the InP. Numerical studies have shown that the proposed algorithm can provide resource isolation and enhance the network throughput by the reuse of resources. Furthermore, we also validate the stability and convergence of the algorithm. As a future extension, we intend to include power control by power allocation for the VNOs with dynamic prices over all the VRs. We would expect to see even more performance gains than those presented here if these extensions are considered.

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