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Cyclic Three-Sided Matching Game Inspired Wireless Network Virtualization

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Abstract—Wireless network virtualization is basically the abstraction, isolation, and sharing of wireless resources among different entities. Consequently, virtualization provides great flexibility and higher network efficiency, and enables easier migration to new technologies in wireless networks. Traditionally, a wireless network virtualization controller manages the virtual resources (including radio resources and infrastructure resources) known as slices which are available to the Service Providers (SPs). The SPs then allocate their purchased resources to serve their subscribed mobile users. Such a centralized allocation decouples the Quality-of-Service (QoS) management by the SPs from the virtual resource management by the controller. In this paper, we propose a matching based wireless network virtualization resource allocation mechanism: a distributed three-sided (3D) matching between radio resources, physical infrastructure and mobile users. The Restricted Three-sided Matching with Size and Cyclic preference model (R-TMSC) is implemented to obtain a stable solution. Simulation results show that our proposed spectrum-oriented and user-oriented algorithms outperform the traditional resource allocation schemes. The spectrum-oriented algorithm enhances the user throughput and the system performance, within a lesser run time. Furthermore, for an increasing number of users, the proposed algorithms serve more users than traditional methods.

Index Terms—Three-sided matching, wireless network virtualization, cyclic preferences.

1 Introduction

VIRTUALIZATION is becoming an increasingly popular concept, applied in many areas such as virtual memory, virtual machines, and virtual data centers [1]. Network virtualization is the technology in which there exists a number of virtual networks, each of which is a partition or aggregation of the underlying physical substrate network [2]. It involves the abstraction, isolation, and sharing of resources among different entities. This enables supporting heterogeneous applications, without having to modify the existing fundamental architecture. As a result, network virtualization offers great network flexibility, maximizes network utilization, and inspires innovation in products and services [3].

The implementation of virtualization in wired networks, such as in virtual private networks, has prevailed for decades. With the current tremendous growth in mobile wireless traffic, due to the massive user numbers and diverse communication content, it is reasonable to extend virtualization to wireless networks. In wireless networks, virtualization involves the sharing of both infrastructure and spectrum resources [4]. Multiple virtual networks can dynamically share the physical substrate networks, leading to better management of resources and lower operational expenses. This paradigm is commonly referred to as wireless network virtualization [1].

Wireless network virtualization decouples the functionalities in networks by separating the roles of infrastructure and service, thus improving the network utilization. In addition, since resource allocation and management are flexible and more dynamic with virtual resources than physical resources, new network technologies can be deployed easily. However, in spite of the vast potential of wireless network virtualization, several design challenges remain to be addressed, which include the isolation, discovery and allocation of resources, mobility and network management, security and so on [1]. In particular, the resource allocation challenge calls for comprehensive efforts, as it decides how the virtual networks are embedded on top of the physical networks, and thus, directly affecting the network utilization.

A popular way of defining the different roles in wireless network virtualization is by classifying them into Infrastructure Providers (InPs), Mobile Virtual Network Operators (MVNOs), Service Providers (SPs), and end users. Even though [1] discusses the role of Mobile Virtual Network Providers (MVNPs), which lease the physical network resources from the InPs and create virtual resources (and may possess spectrum resources as well), along with the MVNOs who operate and assign these virtual resources to the SPs, *MVNOs* has been discussed as a term used collectively to include both MVNPs and MVNOs. Hence, for brevity and to avoid any confusion, we have used the term MVNOs in the latter sense. That is to say, the InPs own the infrastructure

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resources, while the MVNOs own the spectrum resources and are responsible for creating and managing the virtual resources (including both infrastructure and radio resources). The SPs then rent/purchase virtual resources from the MVNOs in a wholesale way, and provide specific services such as VoIP, video streaming, etc., to the end users. In short, virtual resources which exist on physical network infrastructures owned by InPs, are created and managed by MVNOs, and are requested by SPs to serve end users.

A traditional resource allocation solution in wireless network virtualization is to configure the virtual resource/service packages first and then offer the off-the-rack services to the users [5]. Such an approach decouples the virtual service generation procedure, which is accomplished by the MVNOs, from the user service management procedure, which is accomplished by the SPs. A *wireless network virtualization controller* acts as a centralized entity through which the MVNOs manage the virtual resources. Henceforth, we will refer to the wireless network virtualization controller as the *wireless network controller* for brevity, as this work deals only with wireless network virtualization. The centralized allocation of the virtual resources using the wireless network controller lacks the flexibility needed to meet user specific requirements and user mobility. Furthermore, resource allocation solutions are moving from the traditional centralized approaches to more distributed methods, considering the high density, mobility, and self-organizing features of next generation wireless networks like device-to-device (D2D) communication, LTE-unlicensed and so on. Traditional centralized optimization [6] results in high computational complexity and communication overhead, and hence, results in the need for less complex and distributed solutions.

Matching theory has emerged as a promising approach for future wireless resource allocation, by overcoming some limitations of optimization and game theory [7], [8], [9], [10]. The major advantages of matching theory are that we are able to consider individual utilities for the users and the SPs, and that it provides a distributed solution while considering the localized preferences of all the entities [10]. [7] also emphasizes on how the users have preferences on resources and vice versa based on local information, and how the distributed nature of matching takes this into account. It is also highlighted how for every resource allocation problem, there exists at least one stable matching (determined using the Gale-Shapley algorithm) due to the *deferred acceptance* method [11]. [8] highlights the stability aspect of matching theory for a non-regulated scenario, and also how it provides a stable resource allocation compared to competitive methods based on game theory.

Matching is a framework that is based on the formation of mutually beneficial relationships between two sets of entities [12], [13], [14], and provides mathematically yielding solutions based on the preferences of these entities. The advantages of matching theory in wireless resource allocation have been discussed in detail in [15], which include characterizing the behavior of heterogeneous nodes by suitable models, defining general preferences that can manage Quality-of-Service (QoS) related considerations, obtaining stable and optimal solutions satisfying the system objectives, and implementing efficient algorithms at a faster rate.

In this paper, we make use of these advantages of matching theory to integrate the dynamics between all the three elements of abstraction in wireless network virtualization, unlike most of the previous works which dealt mainly with SPs and InPs [16]. Accordingly, we propose a matching-based resource allocation framework for wireless network virtualization, which matches three network elements: spectrum, infrastructure, and end users, simultaneously. Our three-sided matching framework and the corresponding matching-based solution have the following advantages: (a) the conventional centralized resource allocation decouples the virtual service generation procedure by the MVNOs from the user service management procedure by the SPs, which can yield non-optimal results compared to our coupled three-sided matching framework, where all three entities are considered simultaneously; (b) the time-varying nature of spectrum behavior and the changing user requirements demand continuous adjustments in resource allocation, which can be efficiently achieved by the distributed nature of the matching algorithm. The major contributions of this paper are briefly summarized as follows:

- We propose a distributed resource allocation framework for wireless network virtualization, where unlike the conventional decoupled virtual service generation and user service management, we tackle the problem by modeling it as a three-sided matching between radio spectrum, physical infrastructure, and mobile users.
- With joint consideration of user satisfaction, SP revenue, and system cost-performance, we formulate the three-sided matching as an optimization problem, which is NP-hard. Consequently, we model the optimization problem by exploiting the Three-Dimensional Stable Marriage model with Cyclic Preferences (3DSM-CYC), in which each type of agent ranks the other type of agent in its order of preference, and such three preference lists form a cycle[1].
- In order to accommodate virtualization, we consider a variant of the 3DSM-CYC model, the Three-sided Matching with Size and Cyclic preference problem (TMSC), as it allows each agent to have multiple partners. However, since the process of determining whether a stable matching exists for a TMSC model itself is NP-complete, we transform it into a Restricted Three-sided Matching with Size and Cyclic preference problem (R-TMSC) by adding a few plausible restrictions. The R-TMSC model can be solved by the proposed spectrum-oriented and user-oriented R-TMSC algorithms, and a stable solution is always guaranteed. The effectiveness of the proposed algorithm is validated through simulations.

The rest of this paper is organized as follows. We discuss some of the important previous work relevant to our research in Section 2. In Section 3, we present the system framework and assumptions for addressing the resource allocation problem in wireless network virtualization. Here, two important performance metrics are discussed in Section 3.1 and Section 3.2. Then, in Section 4, we formulate the proposed model as an optimization problem, with the objective of maximizing the system cost-performance. The three-sided matching-based approach to solve the optimization problem in a distributed way is explained in Section 5. In this section, we discuss the concept of stability in Section 5.1, the TMSC model in Section 5.2, the R-TMSC model in Section 5.3, the spectrum-oriented R-TMSC model in Section 5.4, and the user-oriented R-TMSC model in Section 5.5. We discuss the performance of the proposed algorithm through simulation results in Section 6. Finally, conclusions are drawn in Section 7.

1. For example, spectrum ranks only user, user ranks only infrastructure and infrastructure ranks only spectrum.

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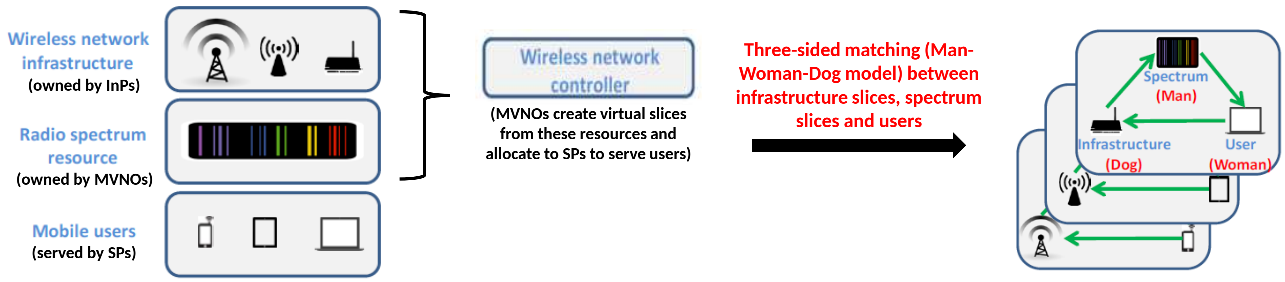

Fig. 1: System model.

2 Literature Review

Since wireless network virtualization is considered to be a feasible method to achieve better spectrum efficiency, higher data rate, and lesser cost per bit in 5G networks [6], [17], a great amount of related research on resource allocation has been going on [18], [19], [20], [21], [22], [23], [24], [25], [26]. A Software Defined Networking (SDN) based framework for resource allocation in wireless network virtualization is proposed in [27], where the allocated resources are adjusted dynamically according to the service requirement and network status variations. [28] proposes an information-centric wireless network virtualization architecture for 5G mobile wireless networks, an important component of which is an efficient virtual resource allocation scheme. A Network Virtualization Substrate (NVS) for optimal virtualization of wireless resources in cellular networks is designed and implemented in [29]. In [30], network slicing in 5G is discussed, where the issue of network resource allocation is dealt with using an algorithm for handling network slice requests. [31], [32] and [33] also discuss network slicing in 5G, focusing on enabling end-to-end network slicing, and on an auction based model for maximizing the network revenue, and on dynamic allocation of network resources to different slices, respectively. Network slicing for Content Delivery Networks (CDN) is discussed in [34]. The application of network virtualization in smart cities, by enabling the use of 5G is discussed in [35]. A user mobility and service usage oriented approach in wireless virtual networks is discussed in [36].

Due to the tremendous potential of matching theory in wireless resource allocation scenarios as discussed in [15], methods to attain optimal resource allocation in wireless network virtualization using matching theory have been prevalent. A novel two-level hierarchical matching algorithm to separately achieve revenue maximization for the InPs and MVNOs has been proposed in [37], by formulating service selection and resource purchasing as a combinatorial optimization problem. The associations between users and Base Stations (BSs) have been formulated as a one-to-many matching game, and a distributed algorithm has been proposed, that results in stable user-BS matchings [38]. [39] also proposes a matching game based resource allocation scheme, simultaneously taking into account the objectives of the InPs and the multiple network operators. In [40], the stable marriage model was employed in the resource allocation problem, to attain matchings between multiple repeaters and vehicle antennas. [41] utilizes matching theory to arrive at stable two-sided matchings between different kinds of files generated by source nodes and relay nodes that forward these files, in Delay Tolerant Networks (DTN). A framework was proposed to find stable matchings of users and resources based on the channel and context aware preference lists in [42]. A route level resource allocation algorithm was proposed for dynamic topology, through a stable and fair allocation utilizing the stable matching algorithm [43]. A framework utilizing matching theory, for Cognitive Radio (CR) networks, was proposed in [44], for content-caching was proposed in [45], and for LTE-Unlicensed (LTE-U) was proposed in [46].

Even though all of the above mentioned works discussed the application of matching theory in wireless network virtualization resource allocation, the optimization for only two sets of entities have been considered at a time for resource allocation: InPs and MVNOs, users and BSs, and so on. Therefore, in this work, we are motivated to address resource allocation in wireless network virtualization by taking into account the three entities of abstraction: radio spectrum, physical infrastructure, and mobile users. This calls for a three-sided matching model, unlike the two-sided matching game that has been exploited mostly in the literature. Consequently, we will be able to couple the virtual service generation by the MVNOs with the user service management by the SPs.

Three-sided matching succeeds in modeling many real life situations like the supplier-firm-buyer model [47] etc. A cyclic three-sided stable matching approach for networking services has been discussed for the first time in [48], where a three-sided matching problem has been formulated, by considering the cyclic three-sided preferences in computer networking systems. The NP-completeness of determining the existence of stable matching has been proved, and a restricted version of the three-sided matching algorithm has been designed. This restricted algorithm has been proved to arrive at stable matchings, and the effectiveness of the algorithm has been shown through simulations in [48].

As discussed above, many of the existing research works have considered two-sided matching games to achieve optimal resource allocation in wireless network virtualization. However, according to the authors' knowledge, a three-sided matching based approach considering the preferences of three sets of entities has not been considered for resource allocation in wireless network virtualization. Therefore, along the lines of the cyclic three-sided matching discussed in [48], we model the typical wireless network virtualization scenario as a three-sided matching game between radio spectrum, physical infrastructure, and mobile users. We propose a restricted three-sided formulation in order to always achieve stable results, and propose spectrum-oriented and user-oriented algorithms to arrive at stable matchings.

3 System Model

As already discussed, in wireless network virtualization, the MVNOs create virtual resources from the physical infrastructure and radio spectrum resources, which are then allocated to the SPs to serve the end users. The infrastructure and radio resources are abstracted and split into *slices* by the MVNOs to facilitate virtualization [4]. These slices are then utilized to serve the users by the SPs, thus ensuring isolation from the underlying physical networks. Traditionally, the virtual resource allocation and management are centrally handled by the wireless network controller, as mentioned in Section 1, which decouples the virtual service generation from the user resource management. Therefore, we propose a distributed resource allocation framework which addresses this issue by modeling the virtual resource allocation as a three-sided matching between the radio spectrum slices, physical infrastructure slices, and mobile users. Even though the proposed approach gives a distributed solution by considering the localized preferences of the parties involved, the wireless network controller can still act as the entity to run the three-sided matching algorithm once the preferences are collected, thus managing the virtual resources.

To this end, we consider a wireless network virtualization scenario as shown in Fig. 1, with a set of K spectrum band slices, $\mathcal{S} = \{s_1, s_2, ..., s_K\}$, and a set of N physical infrastructure slices, $\mathcal{B} = \{b_1, b_2, ..., b_N\}$. For brevity, the spectrum band slices will be referred to as spectrum bands and the physical infrastructure slices will be referred to as infrastructures henceforth. All the spectrum bands are assumed to have identical bandwidth, and the infrastructures include BSs, access points, core network elements and so on. The set of subscribed mobile users is represented by $\mathcal{U} = \{u_1, u_2, ..., u_M\}$, where M is the number of all users subscribed to one particular SP. The three-sided matching between $\mathcal{S}$, $\mathcal{B}$ and $\mathcal{U}$ can be represented by $\mathcal{M} \subseteq \mathcal{S} \times \mathcal{B} \times \mathcal{U}$. Henceforth, we call $\mathcal{S}$, $\mathcal{B}$ and $\mathcal{U}$, the matching agents.

Each spectrum band can be shared between multiple infrastructures, and is limited by its maximum capacity, $q^{s_k} = q^s, \forall k \in \{1, 2, \dots, K\}$ in its allocation to the users. On the other hand, each infrastructure is shared between multiple spectrum bands, and is limited by its maximum capacity, $q^{b_j} = q^b, \forall j \in \{1, 2, \dots, N\}$. In addition, any particular spectrum band assigned to any particular infrastructure can be shared between multiple users. In other words, the matching between the spectrum bands, $\mathcal{S}$, and the infrastructures, $\mathcal{B}$, is a many-to-many matching, while the matching between the (spectrum band ($\mathcal{S}$), infrastructure ($\mathcal{B}$)) pairs and the users, $\mathcal{U}$, is a one-to-many matching.

We begin by defining the performance metrics from the following two perspectives: user experience and SP revenue.

3.1 User Experience

One of the most important aspects of wireless services, which the SPs are concerned about is the user satisfaction or user experience. In order to enhance user satisfaction, we can consider the users' Signal to Interference Noise Ratio (SINR) as the key metric, as it decides the bounds of the channel capacity, and hence, the quality of the wireless service. Since the channel condition primarily depends on the transmitter and the receiver rather than the characteristics of the utilized frequency band, we define user experience as the SINR between the user and the infrastructure. In this paper, we specifically deal with the uplink transmission from the user to the infrastructure. Hence, the SINR will be that received at the infrastructure. It can be represented as

$$\Gamma_{i,j} = \frac{P_{i,j} g_{i,j}}{\sigma_I^2 + \sigma_N^2}, \quad (1)$$

$\forall i \in \{1, 2, \dots, M\}$, and $\forall j \in \{1, 2, \dots, N\}$, where $\Gamma_{i,j}$ is the received SINR of infrastructure b_j from user u_i. $P_{i,j}$ and $g_{i,j}$ are the transmitted power and the channel gain between u_i and b_j, respectively. σ_I^2 represents the channel interference from the other mobile users due to channel reuse, and σ_N^2 represents the channel noise.

3.2 SP Revenue

Another factor that we use to measure the system performance is the revenue that the SPs earn from the users. The mandatory revenue is the incentive that motivates SPs to provide better service to their subscribed users. We assume that each user offers a price based on its desired rate and requirements. Hence, SPs would naturally prefer serving the users with higher offers. We define the SP's revenue, R_{SP}, as the summation of prices offered by the matched users minus the summation of the costs paid to the MVNOs for the matched spectrum resources, which can be represented as

$$R_{SP} = \sum_{u_i \in \mathcal{U}} O_i - \sum_{s_k \in \mathcal{S}} C_k = \sum_{u_i \in \mathcal{U}} \alpha r_i - \sum_{s_k \in \mathcal{S}} C_k, \quad (2)$$

$\forall i \in \{1, 2, \dots, M\}$, and $\forall k \in \{1, 2, \dots, K\}$, where O_i is the price that user u_i offers to all spectrum bands, based on its desired transmission rate r_i, α is the price per Mb/s, C_k is the price paid to the MVNO for spectrum band s_k.

4 Problem Formulation

In the previous section, we discussed two performance metrics, which are both essential for a good resource allocation scheme in wireless virtual networks. The system objective in this paper is designed as a combination of both performance metrics. We define our system objective as the *cost-performance* under the three-sided matching, CP_{sys}, which is represented as

$$CP_{sys} = \frac{\sum CP(i)}{M}, \quad (3)$$

$\forall i \in \{1, 2, \dots, M\}$. Here, the cost-performance of the system, CP_{sys}, is the average of the cost-performance values of all the users, where the cost-performance value of user u_i, $CP(i)$, is given by

$$CP(i) = \frac{\sum \rho_{i,j,k} s_k \log(1 + \Gamma_{i,j}^k)}{O_i}, \quad (4)$$

$\forall i \in \{1, 2, \dots, M\}$, $\forall j \in \{1, 2, \dots, N\}$, and $\forall k \in \{1, 2, \dots, K\}$. Here $\rho_{i,j,k}$ is a binary value, which is equal to 1, if user u_i is utilizing frequency band s_k for its downlink transmission through infrastructure b_j, and 0, otherwise. $\Gamma_{i,j}^k$ represents the actual SINR of user u_i, if matched with infrastructure b_j and spectrum s_k (also considering the interference from other users that share the same s_k and b_j), which is represented as

$$\Gamma_{i,j}^k = \frac{P_{i,j} g_{i,j}}{\sigma_I^2 + \sigma_N^2} = \frac{P_{i,j} g_{i,j}}{\sum_{i' \neq i} \rho_{i',j,k} P_{i',j} g_{i',j} + \sigma_N^2}. \quad (5)$$

Taking (3), (4) and (5) into consideration, we formulate the optimization problem for our scenario, which is expressed as

$$\max_{\rho_{i,j,k}} CP_{sys}, \tag{6}$$

$$\text{s.t.} \sum_{i,j} \rho_{i,j,k} \leq q^s, \tag{7}$$

$$\sum_{i,k} \rho_{i,j,k} \leq q^b, \tag{8}$$

$$\Gamma_{i,j} \geq \Gamma_{min}, \tag{9}$$

$$\rho_{i,j,k} \in \{0,1\}, \tag{10}$$

$\forall i \in \{1,2,\ldots,M\}$, $\forall j \in \{1,2,\ldots,N\}$, and $\forall k \in \{1,2,\ldots,K\}$. Here (6) is the system objective, which aims at maximizing the overall cost performance of the system, which is equivalent to the data rate attained per unit price paid by user u_i. (7) and (8) satisfy the capacity constraints for spectrum s_k and infrastructure b_j, respectively, where $\rho_{i,j,k}$ is the binary value indicating downlink transmission, and q^s and q^b are the maximum capacities of each spectrum and each infrastructure, respectively. (9) states the minimum SINR requirement for the selection of infrastructure b_j by user u_i, where Γ_{min} is the minimum SINR threshold.

Obviously, this optimization problem is a Mixed Integer Non-Linear Programming (MINLP) problem[2], which is generally NP-hard to solve [49]. This motivates us to adopt a feasible sub-optimal solution. Therefore, we introduce the matching-theory based distributed approach, the Three-Dimensional Stable Marriage (3DSM) model, which will be discussed in the next section.

5 Three-sided Stable Matching Game

Three-sided relationships are very common in the social and economic domains, e.g., the supplier-firm-buyer relationship, the kidney exchange problem, and so on. Generally, the three-sided matching can be treated as the three-dimensional generalization of the Stable Marriage (SM) model [13], where the three types of matching agents can be considered as men, women and dogs. This three-dimensional variant of SM is usually referred to as a 3DSM problem. The 3DSM problem, also referred to as the Three Gender Stable Marriage problem, was introduced by Knuth [50].

Primarily, there are two models of the 3DSM problem, depending on the nature of the agents' preference lists. For the first model, each agent might rank in the order of preference, the pairs of other agents that they are ready to form triples with. In the second model, the preference lists of each type of agents include only one type of agents (e.g., men rank only women in the order of preference, women's lists contain only dogs, and dogs rank only men), and is referred to as the 3DSM-CYC problem.

The 3DSM-CYC model was introduced by Ng and Hirschberg [51], as a restriction on the 3DSM model. As an intriguing variant of 3DSM, the 3DSM-CYC problem refers to the case in which the matching agents' preference lists comprise of only one type of agents (instead of pairs of agents). However, the problem of determining whether a given instance of 3DSM-CYC admits a strongly stable matching is NP-complete as studied by [52].

2. The nonlinearity is caused by $\Gamma^k_{i,j}$ in the system objective.

5.1 Stability

Consider the matching $\mathcal{M}$, as mentioned in Section 3. Let $\mathcal{T} = \mathcal{S} \times \mathcal{B} \times \mathcal{U}$ denote the set of all possible triples. Hence, the matching $\mathcal{M} \subseteq \mathcal{T}$, is a set of triples from $\mathcal{T}$. In order to understand the concept of stability for a three-sided matching, we need to understand the idea of a *blocking triple*, which is as given in Definition 1.

Definition 1. ***Blocking Triple in 3DSM:*** *A triple $(s_k, u_i, b_j) \notin \mathcal{M}$, but $(s_k, u_i, b_j) \in \mathcal{T}$, in which each of s_k, u_i, and b_j, prefers triple (s_k, u_i, b_j) to at least one of their current matched partners.*

To elaborate, a blocking triple consists of a spectrum, a user and an infrastructure, each of which has the desire to get matched with each other as a triple, instead of staying with the current matched partners in $\mathcal{M}$. A matching $\mathcal{M}$ is said to be $stable$ if there exists no blocking triple for $\mathcal{M}$ [48].

5.2 TMSC Model

In [48], Cui and Jia studied an interesting variant of the 3DSM-CYC model, the TMSC problem for three-sided networks. TMSC is different from traditional three-sided matching problems, in that it allows each agent to have multiple partners.

We use our spectrum-user-infrastructure instance to explain the TMSC model. In this instance, we assume that spectrums only rank users, users only rank infrastructures, and infrastructures only rank spectrums in their orders of preferences. Each agent can be matched up to a limited number of the other type of agents, that it ranks in the order of preference. The detailed definition of the TMSC model is given in Definition 2.

Definition 2. ***Three-sided Matching with Size and Cyclic Preference Problem (TMSC):*** *The three-sided matching problem of TMSC is to find a matching $\mathcal{M} = \{(s_k, u_i, b_j)\}$ with the maximum cardinality:*

$$\textbf{\textit{max}}\ |\mathcal{M}|, \tag{11}$$

$$\textbf{\textit{s.t.}}\ \mathcal{N}(\mathcal{M}, s_k) \leq q^s, \tag{12}$$

$$\mathcal{N}(\mathcal{M}, u_i) \leq q^u, \tag{13}$$

$$\mathcal{N}(\mathcal{M}, b_j) \leq q^b, \tag{14}$$

$\forall i \in \{1,2,\ldots,M\}$, $\forall j \in \{1,2,\ldots,N\}$, and $\forall k \in \{1,2,\ldots,K\}$, where $\mathcal{N}(\mathcal{M}, x)$ represents the number of partners that x has in the matching $\mathcal{M}$[3]. (11) represents the cardinality of the matching $\mathcal{M}$ (the number of (s_k, u_i, b_j) triples in the matching). (12), (13) and (14) represent the constraints due to the maximum capacities of spectrum, user and infrastructure, s_k, u_i and b_j, respectively. Here, q^s and q^b are as mentioned in Section 3. q^u can be considered as the maximum budget of each user, to purchase services from the SPs.

TMSC is however, NP-hard [48]. Biro and McDermid studied in [52], that the problem of deciding whether a stable matching exists in an instance of the Cyclic 3DSM problem with Incomplete lists (Cyclic 3DSMI) is NP-complete. TMSC is a generalization of the 3DSMI problem according to [48], and hence, the same applies to TMSC.

5.3 R-TMSC Model

As discussed above, even the process of determining whether a stable matching exists for a TMSC model is NP-complete. Hence,

3. Here partner refers to an agent of the type of agents in x's preference list.

we consider techniques to refine the TMSC model to make it easily solvable. Therefore, we add a few reasonable restrictions as given below, and transform the TMSC problem into a Restricted Three-sided Matching with Size and Cyclic preference problem (R-TMSC) problem: (1) The preference lists of spectrums are derived from a master preference list. This master list is the set of all users in strict order (e.g., according to the prices offered), and the preference lists of all spectrums are derived from this master list, including all or just part of it; (2) The infrastructures are indifferent with the spectrums, i.e., for each infrastructure, the spectrums in its preference list form one tie. We refer to this model, satisfying both (1) and (2), as the R-TMSC model. This model will be discussed and modified to be implemented in our wireless network virtualization resource allocation problem. Finding the maximum cardinality matching of the R-TMSC problem is still NP-hard as proved in [48].

Taking the above mentioned restrictions into consideration, we build the R-TMSC model for our scenario. Firstly, we construct the preference lists for each spectrum, user and infrastructure. As mentioned before, in the cyclic preference problem, the preference lists of each type of agents include only one type of agents. Therefore, the preference lists of spectrums consist of only users, users' preference lists contain only infrastructures, and infrastructures' lists are comprised of only spectrums, all in the order of preference.

The preference list of each spectrum over the users is derived from a master list, that ranks the users according to their offer prices, O_i, in descending order[4]. The users who demand higher data rates will offer higher prices, and are more preferred by the spectrums. All spectrums' preference lists are derived from the master list, and in our case, all spectrums create identical preference lists (we assume that all users are acceptable by all spectrums) as

$$PL_s(k,i) = O_i, \tag{15}$$

$\forall i \in \{1, 2, \ldots, M\}$, and $\forall k \in \{1, 2, \ldots, K\}$.

On the other hand, the users rank the acceptable infrastructures according to the service quality (the acceptable set is generated by applying (9)), which is measured by SINR $\Gamma_{i,j}$[5]. The SINR in turn decides the data rates for the wireless service, and thus, the users indirectly choose the infrastructures according to the expected data rates. We denote the preference lists for users as

$$PL_u(i,j) = \Gamma_{i,j}, \tag{16}$$

$\forall i \in \{1, 2, \ldots, M\}$, and $\forall j \in \{1, 2, \ldots, N\}$.

According to the R-TMSC model, the infrastructures are indifferent with the spectrums. In other words, the preference list of any infrastructure consists of a tie, with all spectrums ranked the same, which can be represented as

$$PL_b(j,k) = 1, \tag{17}$$

$\forall j \in \{1, 2, \ldots, N\}$, and $\forall k \in \{1, 2, \ldots, K\}$.

5.4 Spectrum-oriented R-TMSC

After finishing the generation of all the agents' preference lists, we propose our spectrum-oriented R-TMSC algorithm. Slightly different from the R-TMSC algorithm discussed in [48], we tailor it to fit our problem setting. Before moving on to the algorithm, we define the following sets for an instance of R-TMSC and matching $\mathcal{M}$.

$$A^{+1}(\mathcal{M}, s_k) = \{u_i | u_i \succ_{s_k} \mathcal{M}(s_k), u_i \in PL_s\}, \tag{18}$$

denotes the set of all users that spectrum s_k prefers to its current partner $\mathcal{M}(s_k)$.

$$A^{+1}(\mathcal{M}, u_i) = \{b_j | b_j \succ_{u_i} \mathcal{M}(u_i), b_j \in PL_u\}, \tag{19}$$

denotes the set of all infrastructures that user u_i prefers to its current partner $\mathcal{M}(u_i)$.

$$A^{-1}(\mathcal{M}, s_k) = \{b_j | b_j \in \mathcal{B}, s_k \in PL_b, \mathcal{N}(\mathcal{M}, b_j) < q^b\}, \tag{20}$$

represents the set of all infrastructures that still have capacity to accept spectrum s_k.

$$A^{-2}(\mathcal{M}, s_k) = \{u_i | A^{+1}(\mathcal{M}, u_i) \cap A^{-1}(\mathcal{M}, s_k) \neq \emptyset, u_i \in \mathcal{U}\}, \tag{21}$$

represents the set of all users, such that there exists an infrastructure b_j that user u_i prefers to its current partner $\mathcal{M}(u_i)$, and infrastructure b_j still has capacity to accept spectrum s_k.

Also, let $SL_u \subseteq PL_u$, $SL_b \subseteq PL_b$, and $SL_s \subseteq PL_s$, respectively, be sub-lists of agents from the preference lists. We define $Head(SL_u, u_i)$ as the elements (infrastructures) in SL_u with the highest priority. Similarly, $Head(SL_b, b_j)$ and $Head(SL_s, s_k)$ represent the spectrums in SL_b and users in SL_s with the highest priority, respectively.

In light of these definitions, the basic idea of the spectrum-oriented R-TMSC algorithm is to search for the "best" triple and add this triple to the matching $\mathcal{M}$ each time, which starts from an empty set. Each "best" triple (in the form of (u_i, b_j, s_k)) is generated by first selecting a spectrum satisfying certain requirements, and then this selected spectrum chooses the best user that meets its requirements, and finally this selected user picks the most eligible infrastructure. The detailed procedure is described in Algorithm 1.

Algorithm 1 starts with an empty matching $\mathcal{M}$. $\mathcal{U}' = A^{+1}(\mathcal{M}, s_k) \cap A^{-2}(\mathcal{M}, s_k)$, as in line 7, searches for a better triple to improve $\mathcal{M}$. If the *if* statement in line 8 holds true, then the lines till 21 are executed to update $\mathcal{M}$. This is done by selecting a more preferred partner (user) for spectrum s_k as in line 9, and then, selecting a more preferred partner (infrastructure) for that user u_i as in line 11. Finally, this better triple is added to the matching $\mathcal{M}$, as shown in line 20, and this is repeated till we obtain the best triples. This algorithm is called spectrum-oriented R-TMSC matching, since we choose a spectrum first to begin with, and then this spectrum chooses from its list of preferred users, and the users in turn select their preferred infrastructures.

Theorem 1. *The spectrum-oriented R-TMSC algorithm will stop and output a stable matching after a finite number of steps.*

Proof. Algorithm 1 refines a list of triples in each iteration and proceeds by adding the best triple to an initially empty matching $\mathcal{M}$, as in line 20. The $while$ loop goes on till the $flag$ drops to 0. During each iteration, a user u_i is assigned to a better infrastructure b_j in its preference list. Let spectrum s_k be matched to a user, say u_x, but while doing these operations, this $u_x = \mathcal{M}(s_k)$ will be unmatched. Necessarily, u_i is better than u_x for s_k, i.e., $u_i \succ_{s_k} u_x$. Thus, a higher priority user must be matched to a better infrastructure, whenever a matched user becomes unmatched.

4. Here, since it is the SPs who provide services using the purchased spectrum bands, it is basically the SPs that rank the users.

5. We assume the interference, $\sigma_I^2 = 0$ in building the preference lists, since the matching actions of other users are not known in advance to any user.

Algorithm 1 **Spectrum-oriented R-TMSC Matching**

Input: $\mathcal{U}$, $\mathcal{B}$, $\mathcal{S}$
Output: $\mathcal{M}$

Initialization;
Construct the preference lists PL_u, PL_b, and PL_s;
$\mathcal{M} = \emptyset$, $flag = 1$;
while $flag == 1$ **do**
  $flag = 0$;
  for each $s_k \in \mathcal{S}$ **do**
    $\mathcal{U}' = A^{+1}(\mathcal{M}, s_k) \cap A^{-2}(\mathcal{M}, s_k)$;
    if $\mathcal{U}' \neq \emptyset$ **then**
      $u_i = Head(\mathcal{U}', s_k)$;
      $\mathcal{B}' = A^{+1}(\mathcal{M}, u_i) \cap A^{-1}(\mathcal{M}, s_k)$;
      $b_j = Head(\mathcal{B}', u_i)$;
      if $\mathcal{N}(\mathcal{M}, s_k) == 1$ **then**
        $\mathcal{M} = \mathcal{M} \backslash \{\mathcal{M}(s_k), \mathcal{M}(\mathcal{M}(s_k)), s_k\}$;
        $flag = 1$;
      end if
      if $\mathcal{N}(\mathcal{M}, u_i) == 1$ **then**
        $\mathcal{M} = \mathcal{M} \backslash \{u_i, \mathcal{M}(u_i), *\}$;
        $flag = 1$;
      end if
      $\mathcal{M} = \mathcal{M} \cup \{u_i, b_j, s_k\}$;
    end if
  end for
end while
Output stable matching $\mathcal{M}$;

As the number of users, and the number of infrastructures in each user's preference list is limited, the algorithm will stop after a finite number of steps. To prove the stability, let us suppose that the output matching $\mathcal{M}$ from Algorithm 1 is unstable. This implies that there must be a blocking triple (u_i, b_j, s_k) such that: $s_k \in PL_b$, $\mathcal{N}(\mathcal{M}, b_j) < q^b$, $b_j \succ_{u_i} \mathcal{M}(u_i)$, and $u_i \succ_{s_k} \mathcal{M}(s_k)$. So $u_i \in A^{+1}(\mathcal{M}, s_k)$, $b_j \in A^{+1}(\mathcal{M}, u_i)$, $b_j \in A^{-1}(\mathcal{M}, s_k)$, and $u_i \in A^{-2}(\mathcal{M}, s_k)$. Then $A^{+1}(\mathcal{M}, s_k) \cap A^{-2}(\mathcal{M}, s_k) \neq \emptyset$ and $A^{+1}(\mathcal{M}, u_i) \cap A^{-1}(\mathcal{M}, s_k) \neq \emptyset$. The algorithm will not stop in such a case, and hence, this is a contradiction. Therefore, the output matching $\mathcal{M}$ from Algorithm 1 is stable [48]. □

Theorem 2. *The spectrum-oriented R-TMSC algorithm can always find a stable matching in $O(K \sum_{u_i \in \mathcal{U}} |PL_u|)$ iterations.*

Proof. During each iteration of Algorithm 1, at least one user will be assigned to its most preferred infrastructure, if each infrastructure has a large capacity q^b. Hence, the maximum time required for this is decided by the total number of spectrum bands, K, and the total number of users, M, which gives a time complexity of $O(KM)$. However, when q^b is small, at least one user is assigned to a better infrastructure in its preference list during each for loop till the $flag$ becomes 0 and the algorithm terminates. Even in the worst case, each user is pre-matched to all the infrastructures in its preference list, in the order of preference, while the algorithm runs. As a result, instead of M, the lengths of the preference lists of the users decide the maximum time required, resulting in a time complexity equal to $O(K \sum_{u_i \in \mathcal{U}} |PL_u|)$, where $K \sum_{u_i \in \mathcal{U}} |PL_u| \leq |\mathcal{T}|$ ($|\mathcal{T}|$ is the total number of possible triples) [48]. □

Thus, when the number of entities is finite, we can see that the proposed spectrum-oriented R-TMSC algorithm always arrives at a stable matching in a finite number of steps, which is decided by the number of spectrum bands and the lengths of preference lists of the users, as proved in Theorem 1 and Theorem 2. The obtained stable matching implies that none of the spectrum-user-infrastructure triples have entities that prefer other partners to the currently matched partners. This in turn implies that the spectrums (SPs) have been matched to users according to their preferred offer prices, and the users have been matched to infrastructures according to their preferred QoS, in a stable manner (the infrastructures are indifferent with the spectrums, as discussed before). This demonstrates the existence of a feasible algorithm considering the network slices (spectrum and infrastructure resources) as well as the users, simultaneously, with an emphasis on the SP (spectrum) perspective.

5.5 User-oriented R-TMSC

As in the case of spectrum-oriented R-TMSC, we define the following sets for an instance of user-oriented R-TMSC and matching $\mathcal{M}$.

$$A^{+1}(\mathcal{M}, u_i) = \{b_j | b_j \succ_{u_i} \mathcal{M}(u_i), b_j \in PL_u\}, \quad (22)$$

denotes the set of all infrastructures that user u_i prefers to its current partner $\mathcal{M}(u_i)$.

$$A^{+1}(\mathcal{M}, b_j) = \{s_k | s_k \in PL_b, \mathcal{N}(\mathcal{M}, b_j) < q^b\}, \quad (23)$$

denotes the set of all spectrums in the preference list of infrastructure b_j.

$$A^{-1}(\mathcal{M}, u_i) = \{s_k | s_k \in \mathcal{S}, u_i \in PL_s, \mathcal{N}(\mathcal{M}, s_k) < q^s\}, \quad (24)$$

represents the set of all spectrums that still have capacity to accept user u_i.

$$A^{-2}(\mathcal{M}, u_i) = \{b_j | A^{+1}(\mathcal{M}, b_j) \cap A^{-1}(\mathcal{M}, u_i) \neq \emptyset, b_j \in \mathcal{B}\}, \quad (25)$$

represents the set of all infrastructures, such that there exists a spectrum s_k in the preference list of infrastructure b_j, and spectrum s_k still has capacity to accept user u_i.

The other definitions are the same as those in the case of spectrum-oriented R-TMSC. The objective of the user-oriented R-TMSC algorithm is also to search for the best triple and add this triple to the matching each time, which starts from an empty set. Each best triple (in the form of (u_i, b_j, s_k)) is generated by first selecting a user satisfying certain requirements, and then this selected user chooses the best infrastructure that meets its requirements, and finally, this selected infrastructure picks an arbitrary spectrum from its preference list (since we assume plausibly that the infrastructures are indifferent with the spectrums). The detailed procedure is as described in Algorithm 2.

Similar to the spectrum-oriented R-TMSC algorithm, Algorithm 2 starts with an empty matching $\mathcal{M}$. $\mathcal{B}' = A^{+1}(\mathcal{M}, u_i) \cap A^{-2}(\mathcal{M}, u_i)$ as in line 7 searches for a better triple to improve $\mathcal{M}$. If this set $\mathcal{B}' \neq \emptyset$, then the for loop continues to update $\mathcal{M}$. Since we prioritize the users to begin the process, it is called a user-oriented R-TMSC matching. These users then choose from their lists of preferred infrastructures, and the infrastructures in turn select arbitrary spectrums from their preference lists, as they are indifferent with spectrums in R-TMSC.

As in the case of spectrum-oriented R-TMSC, we can easily prove the following for user-oriented R-TMSC:

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Algorithm 2 **User-oriented R-TMSC Matching**

Input: $\mathcal{U}$, $\mathcal{B}$, $\mathcal{S}$
Output: $\mathcal{M}$

Initialization;
Construct the preference lists PL_u, PL_b, and PL_s;
$\mathcal{M} = \emptyset$, $flag = 1$;
while $flag == 1$ **do**
  $flag = 0$;
  for each $u_i \in \mathcal{U}$ **do**
    $\mathcal{B}' = A^{+1}(\mathcal{M}, u_i) \cap A^{-2}(\mathcal{M}, u_i)$;
    if $\mathcal{B}' \neq \emptyset$ **then**
      $b_j = Head(\mathcal{B}', u_i)$;
      $\mathcal{S}' = A^{+1}(\mathcal{M}, b_j) \cap A^{-1}(\mathcal{M}, u_i)$;
      Select arbitrary s_k from $\mathcal{S}'$;
      if $\mathcal{N}(\mathcal{M}, u_i) == 1$ **then**
        $\mathcal{M} = \mathcal{M} \backslash \{u_i, \mathcal{M}(u_i), \mathcal{M}(\mathcal{M}(u_i))\}$;
        $flag = 1$;
      end if
      if $\mathcal{N}(\mathcal{M}, b_j) == 1$ **then**
        $\mathcal{M} = \mathcal{M} \backslash \{*, b_j, \mathcal{M}(b_j)\}$;
        $flag = 1$;
      end if
      $\mathcal{M} = \mathcal{M} \cup \{u_i, b_j, s_k\}$;
    end if
  end for
end while
Output stable matching $\mathcal{M}$;

- The user-oriented R-TMSC algorithm will stop and output a stable matching after a finite number of steps.
- The user-oriented R-TMSC algorithm can always find a stable matching in $O(M \sum_{b_j \in \mathcal{B}} |PL_b|)$ iterations.

Similar to the spectrum-oriented R-TMSC algorithm, the proposed user-oriented R-TMSC algorithm also always arrives at a stable matching in a finite number of steps, which is decided by the number of users and the lengths of preference lists of the infrastructures. The obtained stable matching implies that the users have been matched to infrastructures according to their preferred QoS, and the spectrums have been matched to users according to their preferred offer prices, in a stable manner. This presents another feasible algorithm from the perspective of the users instead of the SPs.

5.6 Convergence

Even though the proposed R-TMSC algorithms are distributed approaches, once the preference lists are created, the matching algorithm can be run offline at an entity like the wireless network controller, and is not iterative. Also, since each entity needs to rank only a few entities which are accessible, the preference lists would not be too long, and the algorithm can converge [48] in a few ms on a large-scale processor (given that the algorithm converged for around 200 users in almost 800 ms in our small-scale processor). However, user mobility can lead to changes in preference lists of different entities. We can either run the three-sided matching algorithm repeatedly, or use algorithms such as the Roth-Vande Vate (RVV) algorithm, which can transform a random matching into a stable matching [46], for dynamically adapting to the changes due to user mobility in our future work.

6 Performance Evaluation

In this section, we evaluate the proposed spectrum-oriented R-TMSC algorithm by comparing it with the user-oriented R-TMSC algorithm, the decoupled allocation, as well as the random allocation, through MATLAB simulations.

The spectrum-oriented R-TMSC algorithm operates by adding a triple to the matching each time, while the triple is generated by finding a qualified spectrum first, and then the best qualified user for this spectrum, and finally the best qualified infrastructure for this user. Similarly, the user-oriented R-TMSC operates by adding one triple each time, but the triple is generated from one qualified user, followed by finding the best qualified infrastructure for this user, and a random qualified spectrum for this infrastructure. We compare the performance of the proposed algorithms with that of a decoupled allocation scheme, which decouples the virtual service generation from the user service management, emulating the traditional centralized allocation by the wireless network controller. For simplicity, we follow the assumption that the infrastructures are indifferent with the spectrums as considered in the R-TMSC scheme, to form spectrum-infrastructure pairs. These resource pairs are then matched with the users using the Gale-Shapley algorithm, which is used to find a stable solution for two-sided matching problems [13]. For comparison purposes, we also consider a random allocation approach, which randomly matches users to spectrum-infrastructure pairs.

We assume a circular cellular network with a radius of $R = 800m$, consisting of $M \in [50, 210]$ mobile users, $N = 5$ infrastructures and $K = 20$ spectrum bands. The bandwidth of each spectrum band is set to be $5MHz$. The capacity of each infrastructure is $44Mbps$, while the capacity of each frequency band is $11Mbps$. The minimum SINR requirements for all mobile users are set at an identical value of $25dB$. For the propagation gain $g = C\beta\zeta d^{-\alpha}$, we set the path loss constant C as 10^{-2}, the multipath fading gain β as the exponential distribution with unit mean, and the shadowing gain ζ as the log-normal distribution with 4 dB deviation and the path loss exponent α as 4.

In Fig. 2a and Fig. 2b, the overall and average throughput of users are evaluated. We increase the user numbers from 50 to 210 by a step size of 20. As shown in Fig. 2a, the network throughput increases under all four schemes as more users join the network. It is reasonable, since spectrum is reused between users who share the same infrastructure and spectrum, which improves the spectrum efficiency. On the other hand, Fig. 2b shows that the average user throughput decreases as more users get matched to the available spectrum and infrastructure resources. It is due to the interference caused by the users who share the same resources. We can also observe from Fig. 2a and Fig. 2b that spectrum-oriented R-TMSC outperforms user-oriented R-TMSC slightly, and both outperform the decoupled and random allocations.

Fig. 3 gives another insight on the system performance from the perspective of user satisfaction. In this paper, we consider the user satisfaction percentage as the ratio between the actual transmission rate and the expected transmission rate. As discussed in Section 1, users make offers to the SPs according to the expected rates. As a result, the users who have higher rate demands will offer higher prices, and thus, are more preferred by the SPs and are better served by allocating resources. It is obvious that as more users join, the user satisfaction decreases. With more users sharing the same radio and infrastructure resources, the interference grows, leading to a performance degradation.

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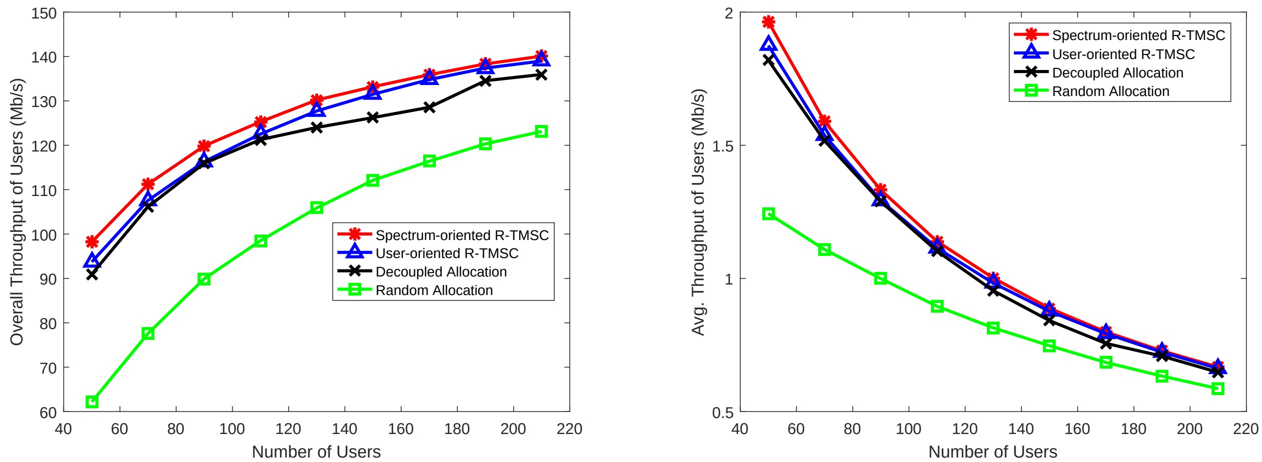

(a) Overall user throughput.

(b) Average user throughput.

Fig. 2: User throughput analysis.

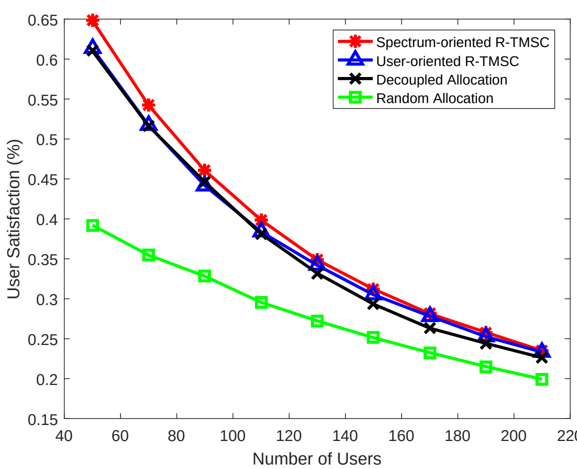

Fig. 3: User satisfaction.

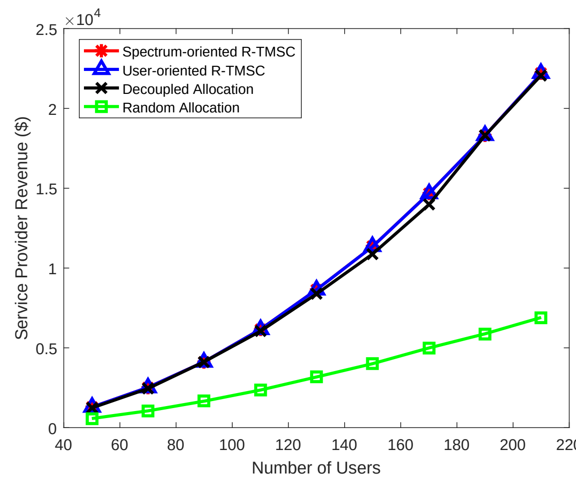

Fig. 4: SP revenue.

However, the spectrum-oriented algorithm still outperforms the user-oriented one, and both demonstrate better results than the decoupled and random allocations.

Fig. 4 compares the four methods in terms of the revenue of the SPs. The SP revenue is calculated as the total income obtained by providing service to matched users using the purchased spectrum resources. Accordingly, more users, more overall revenue. We can see that, apart from random allocation, the other three algorithms achieve more or less the same SP revenue.

In Fig. 5, we analyze the cost-performance of the system. As defined in Section 4, the system objective is to optimize the system cost-performance, which is the actual transmission data rate of each user over its offer price, averaged over all users (average data rate/dollar). The cost-performance metric not only indicates how good the users are performing, but also conveys the benefits earned by the SPs. As can be seen from the figure, it decreases as more users join. This is caused by the average user throughput decrease as indicated in both Fig. 2b and Fig. 3. The spectrum-oriented algorithm again proves itself to be better than the user-oriented algorithm, and both matching algorithms beat the decoupled and random allocations.

Fig. 6 compares the run times of the four algorithms for $M \in [50, 210]$ mobile users, $N = 5$ infrastructures and $K = 20$ spectrum bands. Undoubtedly, the execution time increases as the number of users increases. The difference in run times between the spectrum-oriented algorithm and the other schemes also grows with the number of users. Besides, spectrum-oriented R-TMSC takes $100ms$ less than the other algorithms to finish, which is a huge margin in the wireless communication scenario.

Fig. 7 illustrates the cardinality of the output matching on the number of users, which indicates the number of users served. We increase the user numbers from 50 to 450 by a step size of 20. We can observe from the figure that the spectrum-oriented R-TMSC, user-oriented R-TMSC and the decoupled methods serve all the users, till the number of users is almost 200. Thereafter, the spectrum-oriented and user-oriented algorithms level off at serving around 220 users, as the number of users increases further. This is due to the limited spectrum and infrastructure resources available. The decoupled allocation has a falloff after around 220 users. The random allocation performs poorly throughout.

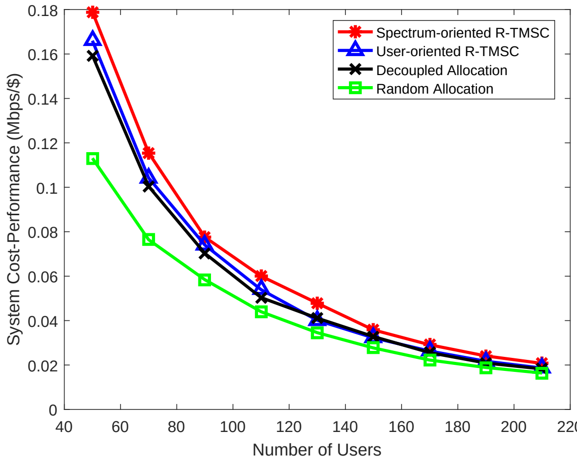

Fig. 5: System cost-performance.

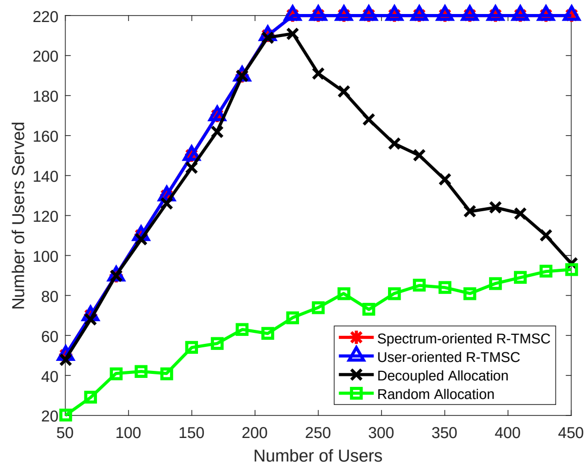

Fig. 7: Cardinality of output matching.

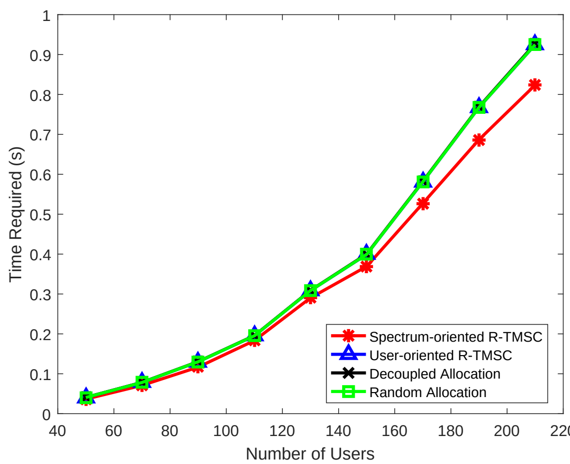

Fig. 6: Algorithm run time.

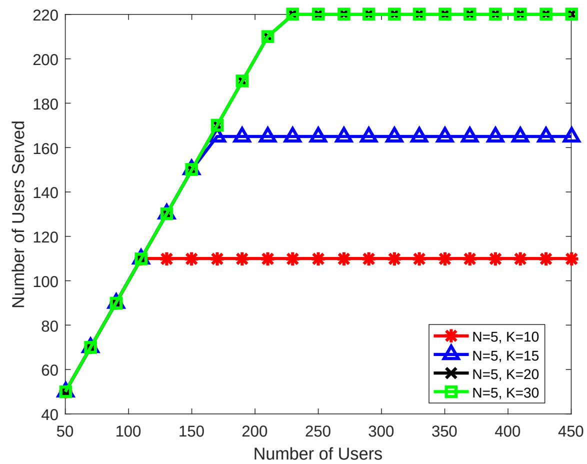

Fig. 8: Cardinality of spectrum-oriented R-TMSC.

Fig. 8 shows the cardinality (number of users served) of the spectrum-oriented R-TMSC algorithm on the number of users for four different cases: $K = 10, K = 15, K = 20$ and $K = 30$. $N = 5$ in all of these cases. It can be noticed from the figure that all the users are served in all four cases, until the number of users reaches a particular value. For the $K = 10$ case, the maximum number of users served is 110, whereas for $K = 15$, it is 165, and it is 220 for the $K = 20$ and $K = 30$ cases. Evidently, for the given number of infrastructures ($N = 5$), as the number of spectrum bands increases, more number of users can be served.

7 Conclusion

In this paper, we propose a matching-based framework for resource allocation in wireless network virtualization. Utilizing a variant of the 3DSM model, the R-TMSC model, we formulate the relations between the radio resources, physical infrastructure and mobile users. The proposed spectrum-oriented and user-oriented R-TMSC algorithms are proved to always generate stable matching results in a finite number of steps. Simulation results validate the effectiveness of the proposed matching-based approaches compared to the traditional centralized methods. The spectrum-oriented R-TMSC algorithm enhances the user throughput and satisfaction, as well as the system cost-performance. It also runs faster than traditional methods, with the run time margin increasing along with the number of users. Moreover, for a given amount of resources, the proposed algorithms serve more number of users than the traditional decoupled and random allocations.

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