User Matching Game in Virtualized 5G Cellular Networks

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***Abstract*—Recently, wireless virtualization has attracted more and more attentions from research communities. With virtualization, resource utilization is higher, system performance is improved and the investment capital is lower. However, there are remaining challenges to be addressed before wireless virtualization is widespread deployed. One challenge is user association which has great influence on the performance of the wireless virtualization network. Traditionally, user associates to the base station (BS) who provides the highest signal to interference plus noise ratio (max-SINR). However, this scheme may not guarantee the quality of service (QoS) of users and backhaul constraint of infrastructure providers (InPs). This motivates us to investigate the user association problem in virtualized cellular networks in this paper. We formulate the user-BS association as a matching game. We show that the preferences used to rank one another are independent and affected by the existing matching. Therefore, this game can be classified as the one-to-many matching game with externalities. In addition, we present a distributed algorithm to find the stable outcome of this game. Simulation results show that the presented association scheme is better than traditional scheme.**

I. Introduction

Due to the growth of smart user devices and traffic demand, the next generation cellular network (i.e. 5G network) requires new information and communication technologies to improve spectrum efficiency, provide higher data rate and reduce the cost per bit [1]. Among several enable technologies for 5G network, wireless virtualization emerges as a feasible approach to achieve the above requirements of 5G network [2].

The basic of virtualization is enabling the resource sharing and separating the infrastructure from the service it provides. The roles between the InPs and mobile virtual network operators (MVNOs) are splitted logically. MVNOs who may not have their own infrastructure have to lease the infrastructure from InPs. Specifically, the physical resources (spectrum bandwidth, backhaul bandwidth) of BSs belonging to an InP are abstracted into virtual resources (i.e. slices). These slices are then shared among different MVNOs. Each MVNOs virtually owns the entire BS with allocated resources provided in the assigned slice. Each MVNO allocates the resources in its slices to its subscribed users. With virtualization, many MVNOs can be coexisted in one InP, and one MVNOs can be operated by many InPs [3].

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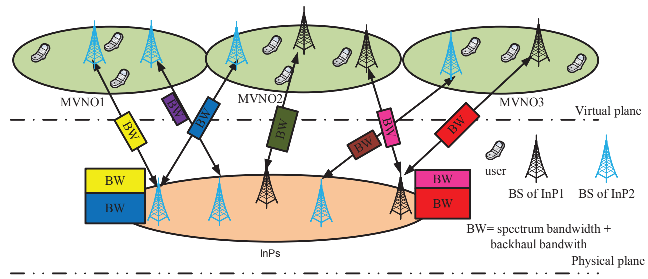

Fig. 1: System model

Virtualization can bring many benefits such that improving the resource utilization, reducing significant the capital expenses (CapEx) and operation expenses (OpEx), decoupling between InPs and MVNOs...In spite of that, there are several significant issues to be addressed, e.g., the isolation, control signaling, user association,resource discovery and allocation schemes, the network management mechanisms. In this paper, we focus on the user association in virtualized cellular network. User association has been studied extensively in [4], [5]. The user association policy must consider both the wireless channel and interference characteristics, as well as the number of users already associated with each BS. However, the authors in [4] just considered the log-utility of user data rates. This paper brings the addition considerations of cost of resource consumption into user association. In addition, different from the existing work in [6] which consider resource allocation in the scenarios of one MVNO using distributed alternating direction method of multipliers, this paper is inspired using matching game as an approach to solve user association where multiple InPs and MVNOs coexist. Recently, matching theory has emerged as a promising approach that can overcome some limitations of game theory and optimization [7]. Matching theory provides tractable solutions for combinatorial problem of matching players in two distinct sets, depending on the individual information and preference of each player.

In this paper, we formulate user association in virtualized cellular network as a matching game. In this game, users and BSs are players that need to rank one another based on the preference functions. The preference functions capture the bandwidth allocation, the cost of bandwidth consumption, QoS requirement and backhaul constraint.Adopting the similar idea in the work [8], we present a distributed algorithm that allows the user-BS to self-organize into a suitable stable user-BS matching.

The rest of this paper is organized as follows. In Section II, we describes the system model and formulate the problem. Section III presents our distributed approach and algorithm to solve the problem. Simulation results are provided in Section IV. Finally, conclusions are drawn in Section V.

II. Problem Formulation

Consider a downlink transmission of a cellular system with multiple InPs as shown in Fig.1. There is a set of $\mathcal{J} = \{1, 2, ...J\}$ BSs belonging to different InPs. InPs provide infrastructure service to a set of $\mathcal{L} = \{1, 2, ...L\}$ MVNOs. Each MVNO $l \in \mathcal{L}$ slices and assigns virtual resources to serving user $i \in \mathcal{I}_l$, which is the set of users of MVNO l. The set of users of all MVNOs is $\mathcal{I} = \cup \mathcal{I}_l$ users. Both the BSs and the users are equipped with a single antenna. Each BS transmits at a fixed power spectrum density (PSD) g_j. The channel from BS $j \in \mathcal{J}$ to user $i \in \mathcal{I}$ is assumed to be flat-fading with channel gain h_{ij}. It has been shown in [4] that at each BS, equal allocation of the available bandwidth among its associated users is optimal in terms of maximizing the log-utility of user data rates. In this case, if user $i \in \mathcal{I}_l$ is associated with BS j, then the instantaneous rate of user i can be written as

$$R_{ij} = \frac{W_j}{K_j} \log(1 + \gamma_{ij}),$$

where K_j is the number of users associated with BS j, W_j is the spectrum bandwidth of BS j and,

$$\gamma_{ij} = \frac{h_{ij} g_j}{\sum_{l, l \neq j} h_{il} g_l + \sigma}$$

is the SINR value of user i if it associated with BS j. Here, σ is the background noise PSD. The proportional fair log-utility of MVNOs earned from serving user can be written as

$$\sum_{i \in \mathcal{I}_l, j} x_{ij} \log(R_{ij}),$$

where $x_{ij} = 1$ if user i is associated to BS j and $x_{ij} = 0$, otherwise. The required backhaul of BS j can be given $\sum_{i \in \mathcal{L}_j} x_{ij} R_{ij} \leq B_j$ where $\mathcal{L}_j$ is the set of users serviced by BS j and B_j is the backhaul capacity of BS j.

With p_l^{bw} units/MHz is the unit price of bandwidth spectrum usage of InP for MVNO l and p_l^{bh} units/Mbps is the unit price of backhaul usage of InP for MVNO l, the cost of MVNO l has to pay for InP is:

$$\sum_{i \in \mathcal{I}_l, j} {p_l}^{bw} x_{ij} \frac{W_j}{K_j} + \sum_{i \in I_l, j} {p_l}^{bh} x_{ij} R_{ij}.$$

The utility of each MVNO depends on both the log-utility of total its users' data rate and the cost of the usage of physical resources. Thus, the problem of maximization the utility of all MVNOs is as follows:

$$\max_{x_{ij}} \sum_{l \in \mathcal{L}} \sum_{i \in \mathcal{I}_l} \sum_{j \in \mathcal{J}} \left(x_{ij} \log(R_{ij}) - {p_l}^{bw} x_{ij} \frac{W_j}{K_j} - {p_l}^{bh} x_{ij} R_{ij} \right) \quad (1)$$

s.t

$$\sum_j x_{ij} = 1, \forall i \in \mathcal{I}_l, l \in \mathcal{L} \quad (2)$$

$$\sum_j x_{ij} R_{ij} \geq {r_{i,l}}^{\min}, \forall i \in \mathcal{I}_l, l \in \mathcal{L}, \quad (3)$$

$$\sum_i x_{ij} R_{ij} \leq B_j, \forall j \in \mathcal{J}, \quad (4)$$

$$x_{ij} = \{0, 1\}. \quad (5)$$

The constraint (1) indicates that user i only associates with one BS at any time. The constraint (2) indicates about the requirement of data rate of user i.

It can be seen that the above maximization problem is combinatorial due to the discrete value of x_{ij}.The complexity of the brute force algorithm is $\Theta(J^I)$, where J and I denote the number of BSs and number of users, respectively. The computation is essentially impossible for even a modest-sized cellular network.In addition, there is a requirement for self-organizing solutions in networks where users and BSs can distributedly decide the best user-BS association, based on their individual objectives. Accordingly, we adopt similar idea of [8]-the idea of using matching game as a tool for developing a self- organizing user-BS association.

III. User Association as a matching game

In this regard, we formulate the problem as a one-to-many matching game between users and BSs. In this game, each user can associate to only one BS, and BS can admit certain quota of users. User and BS rank one another based on their utility function that capture their preferences. These preferences are interdependent and influenced by the existing matching of the same BS. This is call peer effect in externality [7]

Definition 1. A matching game is defined by two sets of players $(\mathcal{I}, \mathcal{J})$ and two preference relation $\succ_i$,$\succ_j$ allowing each player $i \in \mathcal{I}$, $j \in \mathcal{J}$ to build preference over one another, to rank, respectively, the player in $\mathcal{I}$ and $\mathcal{J}$.

The outcome of matching game is a matching function η that bilaterally assign to each players $i \in \mathcal{I}$,a player $j = \eta(i), j \in \mathcal{J}$ and vice versa (i.e, $i = \eta(j)$). Here, a preference relation $\succ$ is defined as a complete, reflexive, and transitive binary relation between the player in $\mathcal{I}$ and $\mathcal{J}$. Thus, for any user i, a preference relation $\succ_i$ is defined over of BSs $\mathcal{J}$ such that, for any two BSs $j, k \in \mathcal{J}^2$, $j \neq k$ and two matching η,$\eta^{'}$ $\in \mathcal{I} \times \mathcal{J}$, $j = \eta(i)$, $k = \eta^{'}(i)$:

$$(j, \eta) \succ_i (k, \eta') \Leftrightarrow U_{j,i} > U_{k,i}, \quad (6)$$

where U is utility of users.

Similarly, for any SBS j, a preference relation $\succ_j$ is defined over of users such that, for any two UEs $i, h \in \mathcal{I}^2$, $i \neq h$ and two matching $\eta, \eta^{'} \in \mathcal{I} \times \mathcal{J}, i = \eta(j), h = \eta^{'}(j)$:

$$(i, \eta) \succ_j (h, \eta') \Leftrightarrow V_{i,j} > V_{h,j}, \quad (7)$$

where V is utility of BSs.

A. Users and BSs' Preferences

The aim of each user (BS) is to maximize its own utility, or equivalently, to become associated to the most preferred BS (users). We try to include constraints in the utility function by applying the penalty function method with

$$\delta_{ij} = \begin{cases} 0, & R_{ij} \geq r_{i^{min}}, \\ 1, & \text{otherwise.} \end{cases}$$

$$\phi_{ij} = \begin{cases} 0, & B_j \geq \sum\limits_{q=i\cup\mathcal{L}_j} R_{qj}, \\ 1, & \text{otherwise.} \end{cases}$$

$$\omega_{ij} = \log(R_{ij}) - p_l{}^{bw}\frac{W_j}{K_j} - p_l{}^{bh}R_{ij}.$$

$$T_j = \sum_{i\in\mathcal{L}_j} w_{ij}.$$

Then, the user's utility is

$$U_{ij} = \omega_{ij} - \kappa\delta_{ij}, \quad (8)$$

where κ is the penalty factor, $\kappa \geq 0$. If the data rate violates the QoS requirement constraint (2), the penalty term κ will reduce the utility. Similarly, the BSs utility is

$$V_{ij} = \sum_{q=i\cup\mathcal{L}_j} w_{qj} - \rho\phi_{ij}, \quad (9)$$

where ρ is the penalty factor for the BSs, $\rho \geq 0$. If the data rate that BSs assign to users associating with that BS exceeds BS's backhauld limit, the penalty term will reduce the utility.

Algorithm 1: User-BS association in virtualized cellular network

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Data: Each UE is initially associated with BS according max-SINR scheme
Result: Convergence to a stable matching η
Phase 1- Initialization
Each user i discovers the BSs in the vicinity ;
Phase 2- Matching
repeat
    Obtain $U_i(\eta)$ and $V_j(\eta)$ for the current matching η and update $D_i = \{U_{i1} \geq ... \geq U_{iz}\}$;
    if $(j, \eta^i_{j,k}) \succ_i (k, \eta)$ **then**
        User i sends a proposal to BS j ;
        BS j computes $V_j^{(\eta^i_{j,k})}$ for swap matching $\eta^i_{j,k}$;
        if $(i, \eta^i_{j,k}) \succ_j (i, \eta)$ *and* $T_j(\eta^i_{j,k}) + T_k(\eta^i_{j,k}) \geq T_j(\eta) + T_k(\eta)$ **then**
            $L_j \leftarrow L_j \cup \{i\}$;
            $L_k \leftarrow L_k$ / $\{i\}$;
            $\eta \leftarrow \eta^i_{j,k}$;
        else
            BS j rejects the proposal, and user i sends a proposal to the next preference;
        end
    end
until *Stable matching*;

Given the formulated user association game, our goal is to find a stable matching, which is one of key solution concepts of matching theory. Because the conventional solution based on deferred acceptance algorithm used in [9] is not suitable to solve matching game with externalities. Here, we look at a new stability concept, based on the idea of swap- matching [10].

Definition 2. Given a matching η, a pair of users $i, h \in \mathcal{I}$ and BSs $j, k \in \mathcal{J}$ with $(i, j), (h, k) \in \eta$, a swap-matching is defined as $\eta^i_{j,k} = \{\eta \setminus (j, i)\} \cup (k, i)$.

A matching is stable if there exist no swap- matchings η^i_{jk}, such that:

$$\forall x \in \{i, h, j, k\}, U_{x,\eta^i_{jk}}(\eta) > U_{x,\eta(x)}(\eta) \text{ and}$$

$$\exists x \in \{i, h, j, k\}, U_{x,\eta^i_{jk}}(\eta) \geq U_{x,\eta(x)}(\eta).$$

A matching η with link $(i, j) \in \eta$ is said to be stable if there are not any user h or BS k that user i prefers BS j to BS k or any BS j prefers user h to i. Such network-wide matching stability is reached by guaranteeing that swaps occur if they are beneficial for the involved player (i.e. $\{i, j, h, k\}$), given the externalities in the current matching η.

In a swap matching η, if there is an increasing the utility for any of players in $\{i, j, h, k\}$ without decreasing the utility for the other player, a user i can switch from BS j to BS k. Through swap matching, the order of preferences for each player not involved in the swap is unaltered. Hence, no player has an incentive to swap from its current association, leading to a network- wide stable user association.

B. Algorithm

We propose Algorithm 1 to find a stable matching for user association problem in (1). The algorithm is a two-phase process. The first phase is the initialization phase. Firstly, each user is associated to BS j who provides the highest SINR (max-SINR). The second phase is matching phase. Based on current matching, each user sorts its vicinity BSs in decreasing order according to its respective utility function in (8). If BS j is not the most preferred BS of user i, user i will propose to its the most preferred BS (denote by k). Upon receiving proposals from users, BS k will accept user i if 3 conditions are satisfied simultaneously: new matching makes the BS k' utility in (9) is increased most, sum of total utility (not include penalty functions) of the BS j and k (i.e. $T_j(\eta^i_{j,k}) + T_k(\eta^i_{j,k}) \geq T_j(\eta) + T_k(\eta)$) is increased and the order of preference lists of other users already served by their most preferred BSs. Otherwise, if user i is rejected by BS k , user i will propose to the next BS in its preference list. Both users and BSs periodically update their respective utilities and preferences according to the current matching and ensure that they are associated to their respective first preference.

Because there are limited number of vicinity BS for each user, the number of possible swaps are limited. Additionally, when phase 2 ends, each user remains connecting to the most preferred BS, and vice versa. Therefore, we can conclude that Algorithm 1 is guaranteed to achieve stable matching.

IV. Simulation Results

To evaluate the performance of the proposed user association algorithm, we simulate system of two InPs and three

TABLE I: Simulation Parameters

Parameter	Value
Bandwith	20MHz
Noise power	-174dBm/Hz
Backhaul Capacity	10 Gbps for marco BS, 2 Gbps for small BS
Transmit Power	49 dBm for marco BS, 25 dBm for small BS
QoS requirement	MVNO1,MVNO3: 300kps; MVNO2: 400kps
Shadowing	log normal as (N, σ^2), $\sigma = 8dB$ for marco BS $\sigma = 4dB$ for small BS

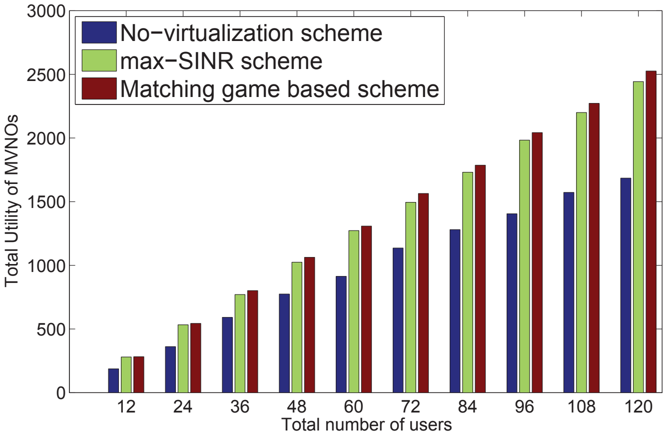

Fig. 2: The total utility of MVNOs in the system

MVNOs. The first InP has 1 marco BS and 10 small BSs, the second InP has 10 small BSs. The average number of scheduled users of three MVNOs are equal. The location of the marco BS is fixed in the center and location of 20 small BSs are uniformly distributed in a area where the radius is 250 meter representing urban enviroment. The basic simulation parameters are shown in Table I. The path loss between marco BS and user, small BS and users is $L(d) = 34 + 40log(d)$ and $L(d) = 37 + 30log(d)$, respectively.

To compare our matching game based scheme, two benchmarks are considered. The first is the no virtualization scheme where each MVNO has the fixed infrastructure resource. Here, each MVNO has 7 BSs with full bandwidth. The second baseline is a traditional max-SINR association scheme where all user associate to the BSs who provide the maximum received SINR, and each BS performs proportional fairness resource allocation. We first consider the total utility of MVNOs achieved by different algorithm as shown in Fig.2. We can see that there is increasing in the utility of MVNO when the number of users increases. This is because the proportional fair log-utility of MVNOs achieved from serving users increases while the payment for InPs is unchanged. Also, we can observe that the matching game based scheme gives better performance when comparing with the no-virtualization and max-SINR scheme. Fig.3 shows the convergence time of the proposed algorithm, as the number of users grows. The number of iterations of proposed algorithm is expected to increase with the network size. However, the convergence time increases linearly as the number of users grows, thus, yielding a reasonable complexity.

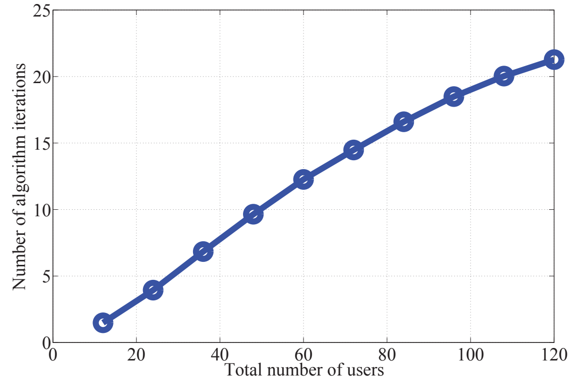

Fig. 3: The number of iterations

V. Conclusion

In this paper, we have formulated user association in virtualization cellular network as a matching game which captures the preference, QoS requirement and backhaul constraints from users and BS. In this matching game user and BS are players that rank one another according to their preferences. The preferences here are interdependent and affected by the existing matchings. To solve the game, we also have presented a distributed algorithm that accounts for network externalities. The simulation results have showed that the proposed scheme is better than traditional max-SINR scheme and no virtualization scheme.

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