IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 19, 2020, accepted April 4, 2020, date of publication April 15, 2020, date of current version April 30, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2987753

Distributed Radio Slice Allocation in Wireless Network Virtualization: Matching Theory Meets Auctions

DO HYEON KIM[1], S. M. AHSAN KAZMI[1,2], ANSELME NDIKUMANA[1,3], AUNAS MANZOOR[1], WALID SAAD[1,4], (Fellow, IEEE), AND CHOONG SEON HONG[1], (Senior Member, IEEE)

[1]Department of Computer Science and Engineering, Kyung Hee University, Yongin 17104, South Korea
[2]Networks and Blockchain Laboratory, Secure System and Network Engineering, Innopolis University, 420500 Innopolis, Russia
[3]Faculty of Computing and Information Sciences, University of Lay Adventists of Kigali, Kigali, Rwanda
[4]Wireless@VT Group, The Bradley Department of Electrical and Computer Engineering, Virginia Tech, Blacksburg, VA 24061, USA

Corresponding author: Choong Seon Hong (cshong@khu.ac.kr)

This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the Grand Information Technology Research Center support program (IITP-2020-2015-0-00742) supervised by the IITP (Institute for Information & communications Technology Planning & Evaluation) and partially supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (No. 2015-0-00567, Development of Access Technology Agnostic Next-Generation Networking Technology for Wired-Wireless Converged Networks).

ABSTRACT Wireless network virtualization has been introduced to satisfy the ever-increasing user requirements through resource sharing, and it can reduce operating costs for the network. Virtualized resources of an infrastructure provider can be allocated as slices to mobile virtual network operators to satisfy their users' demands. Thus, an efficient resource allocation method is needed. Furthermore, existing works have mostly considered resource allocation methods using one infrastructure provider in the system model. However, in realistic and practical environments, multiple infrastructure providers should be considered so that the mobile virtual network operator can choose the appropriate infrastructure provider to maximize its revenue. Therefore, in this paper, a new approach based on matching theory and auctions is proposed for slice allocation for a system with multiple infrastructure providers. Moreover, a matching algorithm and an auction are utilized to work as the distributed methods for solving the user association problem and slice allocation problem, respectively. To connect these two problems, the user association result is used as an input of the auction model so that the mobile virtual network operator can decide on the appropriate infrastructure provider to submit the bidding value. Simulation results show that the developed solutions achieve stable matching and maximize the social welfare of all bidders.

INDEX TERMS Matching game, auction, resource allocation, winner determination problem, price determination problem, wireless network virtualization.

I. INTRODUCTION

The demand for wireless network capacity has exponentially increased over the past decade and will continue to do so in the foreseeable future. This, in turn, exacerbating the challenges of meeting the demand of emerging and heterogeneous wireless services. Furthermore, the traffic model of each wireless service can have a particular demand based on the service characteristics (e.g., queuing system, traffic arrival process, and distribution of transmission time). Thus, an efficient resource allocation scheme is needed to guarantee the quality-of-service (QoS) and user demands. In addition, to manage the cost of the network such as capital expenditure (CAPEX) and operational expenditure (OPEX), infrastructure and radio resources need to be shared by multiple mobile network operators (MNOs). Therefore, wireless network virtualization (WNV) is an encouraging solution to share network resources and attain the requirement of next generation (5G) networks, i.e., to provide higher data rates, minimize latency, and support massive amounts of

The associate editor coordinating the review of this manuscript and approving it for publication was Fang Yang.

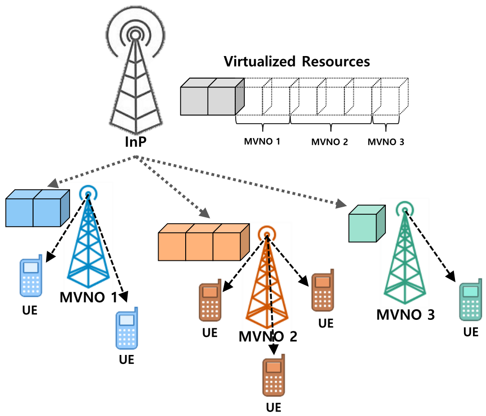

FIGURE 1. Virtualized resource allocation in WNV [11].

data [1], [2]. In addition, WNV can be considered to provide the new business opportunities to InPs, MNOs, and mobile virtual network operators (MVNOs) to make profits and build flexible network operation strategies via resource sharing [3], [4]. The authors in [5] studied the challenges of network slicing and virtualization in next-generation networks. In addition, they introduced a new architecture for flexible network management in the multi-tenant networks. Moreover, they proposed a game-theoretic framework to study the performance and financial benefit offered by efficient infrastructure sharing. The results in [5] showed that network slicing can provide the required performance and necessary incentives for network toward 5G. For this reason, many papers have looked into optimal resource allocation and pricing methods. In [6], a spectrum sharing scheme was proposed to maximize the spectrum utilization in a multi-tenant network. By using WNV, the spectrum bandwidth can be partitioned as the virtual resources, and the network infrastructure operator allocates the resources to various tenants having their own service requirements. In [7], the authors proposed a virtual resource sharing scheme in a WNV environment, which is composed of one MNO and multiple wireless service providers. To maximize network profit at an equilibrium price for the virtual resource, they considered market equilibrium theory. In [8], the authors considered a price-based solution for power resources by using a WNV transmission system, where spare power can be shared with several virtual network operators (VNOs) for InPs' revenue maximization. Furthermore, a noncooperative game was formulated for the selection of VNO's strategy to maximize each VNOs' utility by finding the equilibrium point. Moreover, a matching game based resource allocation method was proposed in [9] under the scenario of one InP. In [10], the Stackelberg game was used for finding optimal pricing of resource allocation in wireless network virtualization. As we mentioned above, for the system models in [6]–[10], the authors did not consider resource sharing with multiple InPs. In contrast, here, we consider multiple InPs with multiple MVNOs and users to investigate the resource allocation problem in a more practical and realistic environment.

Matching theory is a renowned technique from game theory that provides a useful mathematical framework for studying various wireless networking problems [12]–[18]. The authors in [19] proposed a matching-based flow prioritization algorithm to ensure the quality of service of over-the-top (OTT) applications (e.g., YouTube, Skype, etc.). By using a virtual controller, the information for virtual slice allocation is collected and the matching is performed between the resources and corresponding application based on flow prioritization. As a result, the proposed algorithm achieved a better grade of service (GOS) and delay performance. In [20], a matching game has been considered to maximize the probability of serving the UEs under their rate thresholds in shared LTE-A network environment. Unlike the related works for matching approach in [19], [20], we consider a distributed resource allocation scenario with multiple network infrastructure providers. Moreover, our proposed matching scheme involves a variable quota instead of a static quota. In our previous work [21], we also have shown that the matching-based scheme efficiently performs the resource allocation to the set of users. However, in [21], no pricing mechanism was considered and we assumed that the resource price was the same. Here, we extend the idea of our previous work [22] from a single InP scenario to a more practical mutliple InP network. Typically, a practical deployment of a WNV will have a multi-cell scenario in which a set of InPs will serve a specific region. Thus, solutions developed for a single InP scenario will fail and a new solution would be required considering the multi-InP network. Therefore, we propose effective resource sharing and price determination scheme that is suited for a multi-InP network opposed to our previous works.

In a wireless system, an auction mechanism is used for radio resource allocation as an economic and business management approach [23]. By using pricing scheme based on auction mechanism, resource such as sub-channel is efficiently and dynamically allocated between buyers and sellers in a market scenario [3]. In [24], the authors used a power allocation method to share resources in a physical access point for a virtualized wireless network by using an auction that is based on the McAfee mechanism to maximize the transmission rate. In the system model in [25], a hypervisor was introduced between the InP and several MVNOs to make several virtual evolved Node Bs (eNBs); this has the responsibility to schedule the resource blocks among different virtual slices. In the proposed system model, resource block allocation was modeled by a Vickrey Clarke Groves (VCG) auction [26].

Here, we assume that the communication resources of InPs are scarce. Therefore, the auction drives competition between MVNOs for obtaining resources and allows the InP to sell resources with the price that maximizes its revenue. The authors in [27] highlighted that 5G networks will support a wide range of use cases such as enhanced mobile broadband, ultra-reliable low latency communications, and massive machine-type communications with diverse service requirements, with network slicing being one of the key enabling technologies of 5G. Furthermore, the use of auction mechanisms in slice allocation has become an important topic in the recent literature that focuses on the economic aspects of networks [3], [27]–[29]. This is because auction mechanisms can support individual rationality, incentive compatibility, fairness, efficiency, revenue maximization, and social welfare maximization [30]–[32]. However, by considering multiple MVNOs, centralized auction mechanisms are inefficient due to the complexity associated with collecting bidding values from MVNOs and available resources from InPs for running the auction. The authors in [3] showed that a centralized auction mechanism lacks scalability and becomes a single point of failure. To avoid the single point of failure of a centralized auction, a distributed auction can be considered. In a distributed auction, self-interested agents determine outcomes instead of using one centralized agent [33]. Here, without using a centralized auctioneer, each InP manages its auction for the resources and determines the auction's outcome. The authors in [32] and [34] proposed distributed auctions for resource allocation. However, works in [32] and [34] do not investigate the problems of user and slice association. Moreover, they only consider a network a single InP. In contrast, we propose a new approach based on matching theory for user association and auctions for slice allocation, while considering multiple InPs that act as sellers of resources and multiple MVNOs acting as buyers. Also, the authors in [35] demonstrated that the resource allocation that maximizes social welfare can be realized by using Vickrey–Clarke–Groves (VCG) mechanism. Therefore, in our approach, we use the VCG mechanism. In [36], the authors proposed a hierarchical combinatorial auction for a single-seller and multi-buyer case, and a multi-seller and multi-buyer case. They solved the resource allocation problem in a system model that consists of two layers (MVNOs with users in the lower layer and InPs with MVNOs in the upper layer) for the single-seller and multi-buyer case. This was extended to provide a solution for the multi-seller, multi-buyer case. In addition, they introduced a broker for each layer as the auctioneer in the multi-seller and multi-buyer case. In [37], the authors proposed a combinatorial double auction for dynamic multi-dimensional physical resources allocation to maximize the social welfare between multiple MVNOs and users. However, the proposed combinatorial double auction model has an auctioneer as the auction controller, who has the responsibility to collect the bids and allocate the resources to the winners. In this case, the valuation, which includes private information from bidders (buyers), should be gathered by the auctioneer in a centralized manner. Compared to the aforementioned work, the main contribution of this paper is a distributed auction approach to consider the multiple InPs and MVNOs as buyers and sellers. Furthermore, our approach considers the result of matching game to calculate the users' demand and does not require an external broker, i.e., an auctioneer. In our approach, each InP performs its auction, which avoids the charges that InPs and MVNOs usually have to pay the auctioneer; these charges can cause the prices of slices to increase. In addition, our approach reduces the complexity of the existing centralized auction process, which requires an auctioneer to collect bidding values from MVNOs and available resources from InPs to find the winners of the auction for each InP's resource. Finally, to ensure that our proposed auction is conducted in a fair manner, we prove that our proposal guarantees truthful bidding and individual rationality, i.e., increases social welfare.

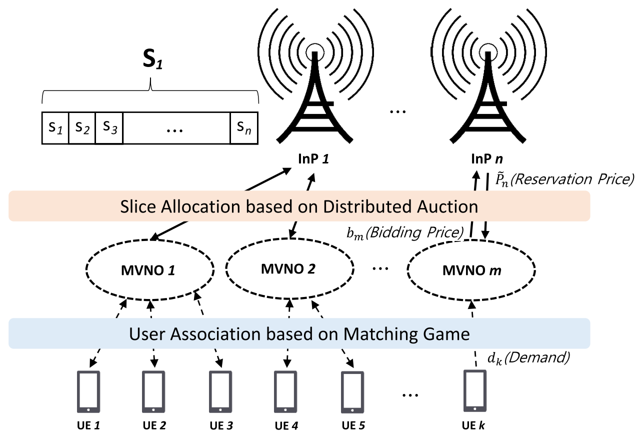

FIGURE 2. System model.

The rest of this paper is organized as follows. We introduce our system model and the problem formulation in Section II. In addition, we describe the proposed solution approaches of the formulated problem for slice allocation in Section III. In Section IV, we present our simulation results for the proposed methods. Finally, in Section V, the conclusions are drawn.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we described in details our system model and problem formulation.

A. SYSTEM MODEL

In our system model shown in Fig. 2, we consider the downlink of the cellular network. In addition, the system model has a set of $\mathcal{N}$ base stations and each base station represents an InP. InP network consists of a base station as a physical substrate and a spectrum so that slices are produced according to the requests from MVNOs and assigned to users. Each InP has a responsibility to support a set of $\mathcal{M}$ MVNOs for their users' demands. Moreover, MVNO $m \in \mathcal{M}$ uses the slices which are bought from the chosen InP to satisfy the demand for a set $\mathcal{K}_m$ of associated user equipment (UEs). Furthermore, $\mathcal{K}$ represents a set of all the UEs in the network such that $\mathcal{K}_m \subset \mathcal{K}$ and notation $|\mathcal{K}|$ denote by the cardinality of a set $\mathcal{K}$.

In the channel model for each InP, we consider orthogonal channels presented by a set of $\mathcal{C}_n$ with bandwidth W. Furthermore, we assume fixed interference combined in the background noise σ^2 stemming from other InPs. Moreover, equal power is considered for all channels in the InP n,

TABLE 1. The summary of key notations.

Notation	Description
$\mathcal{N}$	A set of InPs
$\mathcal{M}$	A set of MVNOs
$\mathcal{K}_m$	A set of user equipment associated to MVNO $m \in \mathcal{M}$
$\varepsilon_n^{\max}$	Maximum power of an InP n
$R_{n,k}^{s_n}$	The data rate for an MVNOs' UEs $k \subseteq \mathcal{K}_m$ on a slice s_n
$U(\boldsymbol{x},\boldsymbol{y})$	The utility of InP
$x_{k,m}$	Association variable for user and MVNO m
$y_{n,m}^{s_n}$	Slice allocation decision variable of MVNO m for slice s_n
$V_m(s_n)$	Valuation of MVNO m for slice s_n
b_m	Bidding values of MVNO m
$V_n(\mathcal{S}_n)$	Valuation of InP n for slice $\mathcal{S}_n$
$V_{\mathcal{M}}$	Maximum valuation of all MVNOs
$\widetilde{P}_n$	Reservation price for InP
P_n^*	Optimal price for slice d_m
U_m	The utility of MVNO m

i.e., $\varepsilon_n = \frac{\varepsilon_n^{\max}}{|\mathcal{C}_n|}$, ε_n represents the power for each channel and $\varepsilon_n^{\max}$ denotes the maximum power of an InP n. In addition, we assume that specific services are provided by an InP n through a set of $\mathcal{S}_n$ slices and each slice $s_n \triangleq \{c \in \mathcal{C}_n\}$ includes the heterogeneous number of channels based on MVNO users' demands. In a WNV, resource isolation can be considered based on two different levels (e.g., flow level and physical resource level) [38]. In the physical level isolation that we consider, it is possible to achieve better resource utilization than higher level isolation at the cost of higher computational complexity [36]. Furthermore, the implementation scheme for physical resource level isolation can be done in two different ways. The first is a static fixed sharing scheme and the second is a dynamic general sharing scheme. In the static fixed sharing scheme, a fixed subset of physical resources in different domains is preassigned by MVNOs. Moreover, access is restricted within this fixed subset. In contrast, in the dynamic general sharing scheme that we adopt, isolation is conducted by ensuring certain predetermined requirements with no restriction for resource access. Based on these isolation perspectives, as shown in Fig. 1, virtualized resources of the infrastructure provider (InP) can be shared with MVNOs to ensure network connectivity and increase the efficiency of resource utilization [5].

We define the binary variables $y_{n,m}^{s_n}$ for the slice allocation and $x_{k,m}$ for the user association. Therefore, $y_{n,m}^{s_n}$ and $x_{k,m}$ can be described as follows:

$$y_{n,m}^{s_n} = \begin{cases} 1, & \text{if slice } s_n \text{ is allocated to MVNO } m \text{ from InP } n, \\ 0, & \text{otherwise.} \end{cases}$$

$$x_{k,m} = \begin{cases} 1, & \text{if user } k \text{ is associated with MVNO } m, \\ 0, & \text{otherwise.} \end{cases}$$

The rate for an MVNO UEs $k \subseteq \mathcal{K}_m$ on a slice s_n is given by:

$$R_{n,k}^{s_n} = \sum_{c \in s_n} W \log_2(1 + \gamma_{n,k}^c). \tag{1}$$

The channel gain between UE k and InP n represented by $g_{n,k}^c$ in notation $\gamma_{n,k}^c = \frac{\varepsilon_n g_{n,k}^c}{\sigma^2}$.

In network virtualization, to maximize the InPs and MVNOs' revenues, we need to minimize network cost. However, here, we focus on maximizing the InPs and MVNOs' revenues by efficiently allocating resources to satisfy users' demands[1] In our model, each InP sells the resource with price p_n per unit of the slice to the MVNO. The objective of InP is to maximize its revenue under the optimal price as well satisfying the users' demands. Thus, we define the system utility as follows:

$$U(\boldsymbol{x},\boldsymbol{y}) = \sum_{m \in \mathcal{M}} \sum_{s_n \in \mathcal{S}_n} \sum_{k \in \mathcal{K}_m} x_{k,m} y_{n,m}^{s_n} (R_{k,m}^{s_n} + \omega p_n s_n), \tag{2}$$

(2) represents the utility of each InP which is composed of the data rate summation of the network and the revenue of the InP. In (2), the weighting parameter ω captures the tradeoff between network data rate and the revenue of InP. Moreover, the weighting parameter is decided by an operator based on their operational strategy.

B. PROBLEM FORMULATION

The objective of wireless network virtualization is to achieve the maximum system utility from the perspective of the InP and MVNO's users. In other words, maximizing the InPs' revenues and satisfying the demands of users are the main target. Thus, the network slice allocation problem is formulated as follows:

$$\mathbb{P} : \max_{\boldsymbol{x},\boldsymbol{y}} \sum_{n \in \mathcal{N}} U(\boldsymbol{x},\boldsymbol{y}) \tag{3}$$

$$\text{s.t.} \sum_{m \in \mathcal{M}} x_{k,m} \leq 1, \quad \forall k \in \mathcal{K}, \tag{3a}$$

$$\sum_{k \in \mathcal{K}_m} \sum_{s_n \in \mathcal{S}_n} x_{k,m} y_{n,m}^{s_n} \leq \mathcal{S}_n, \quad \forall k \in \mathcal{K}_n, \tag{3b}$$

$$\sum_{s_n \in \mathcal{S}_n} x_{k,m} y_{n,m}^{s_n} R_{n,k}^{s_n} \geq d_k, \quad \forall n \in \mathcal{N}, \tag{3c}$$

$$y_{n,m}^{s_n} b_m \leq \widetilde{P}_n, \quad \forall m \in \mathcal{M},\ n \in \mathcal{N}. \tag{3d}$$

For the InP, $y_{n,m}^{s_n} \in \mathcal{Y}$ is the binary decision variable for the slice selection, where $y_{n,m}^{s_n} = 1$ indicates that MVNO m is accepted by InP n for slice s_n, and d_k represents the demand of UE k. Given this problem formulation, constraint (3a) guarantees that each user can be only associated with one MVNO. In addition, we ensure that the number of allocated slices is less than the total usable slices in the entire network through constraint (3b). The minimum data rate

[1] The MVNO's revenue is captured by the maximum data rate based on (1).

Algorithm 1 User Association Algorithm

Input: $t = 0, q_m(0) = |\mathcal{S}_m|, p_k^{m(0)} = p_k^m, p_m^{(0)} = p_m, \forall\, k, m$

repeat
  $t \leftarrow t + 1$
  $\forall\, k \in \mathcal{K}_{\mathcal{M}}$, *propose to m according to* $p_k^{m(t)}$
  while $k \notin \beta(m)^{(t)}$ and $p_k^{m(t)} \neq \emptyset$ **do**
    if $q_m^{(t)} \geq |\gamma_{m,k}|$ **then**
      $p_m^{'(t)} = \{k' \in \beta(m)^{(t)} | k \succ_m k'\}$
      $k'_{l_p} \leftarrow$ *the last preferred* $k' \in p_m^{'(t)}$
      while $(p_m^{'(t)} \neq \emptyset \cup q_m^{(t)} \geq |\gamma_{m,k}|)$ **do**
        $\beta(m)^{(t)} \leftarrow \beta(m)^{(t)} \backslash k'$
        $p_m^{'(t)} \leftarrow p_m^{'(t)} \backslash k'_{l_p}$
        $q_m^{(t)} \leftarrow q_m^{(t)} + |\gamma_{k',m_{l_p}}|$
        $k'_{l_p} \leftarrow k' \in p_m^{'(t)}$
      end while
      if $q_m^{(t)} \geq |\gamma_{m,k}|$ **then**
        $p_m^{''(t)} = p_m^{'(t)} \cup \{k\}$
      else
        $\beta(m)_{(t)} \leftarrow \beta(m)^{(t)} \cup \{k\}$
        $q_m^{(t)} \leftarrow q_m^{(t)} - |\gamma_{m,k}|$
      end if
      for $l \in p_m^{''(t)}$ **do**
        $p_l^{m(t)} \leftarrow p_l^{m(t)} \backslash \{m\}$
        $p_n^{(t)} \leftarrow p_n^{(t)} \backslash \{l\}$
      end for
    else
      $\beta(m)^{(t)} \leftarrow \beta(m)^{(t)} \cup \{k\}, q_m^{(t)} \leftarrow q_m^{(t)} - |\gamma_{m,k}|$
    end if
  end while
until $\beta^{(t)} = \beta^{(t-1)}$

Output: $x \leftarrow \beta^*$

for all UEs k is ensured by isolation constraint (3c) and constraint (3d) guarantees that the minimum bidding value of each MVNO must be greater than or equal to the reservation price of each InP. The optimization problem in (3) is an integer linear programming problem and has a combinatorial structure [24], [25]. Due to the heavy computation problem, solving an optimization problem of this type by using a centralized method is difficult [39]. In addition, a centralized approach for network resource management can occur the scalability issues because more information exchange between the central node and local node is required [40]. Thus, we aim to provide a distributed approach as the solution to cope with the aforementioned issues.

III. SOLUTION APPROACH

For the aforementioned problem, (3) is an integer linear programming (ILP) problem, which is NP-hard. Therefore, to solve it, we decouple the problem into two parts and present two-phased solutions to solve the problem. Moreover, we also show how to connect these two solutions to address the overall problem. In the first phase, a matching game based solution between users and MVNOs is proposed to find the best user association by using users' preference profile. In the second phase, using output of the first phase, we propose a distributed auction based mechanism for InPs to find the winners and optimal price for the demanded resources from MVNOs. Finally, we run these phases iteratively to find the solution of the proposed optimization problem in a distributed fashion. The merit of this solution approach over other existing approaches (e.g., branch-and-bound), pertains to the fact that it allows decomposing the formulated into small sub-problem, where each sub-problem can be addressed using the appropriate approach.

A. MATCHING GAME FOR USER ASSOCIATION

For the association between MVNOs and users, we use a matching game approach. In our matching game, we consider that each user can only be associated with one MVNO and each MVNO can support multiple users. Thus, this matching game is called the one-to-many matching game for user association.

Formally, a matching β is denoted by a function from the set $\mathcal{K} \cup \mathcal{M}$ into the set of elements of $\mathcal{K} \cup \mathcal{M}$, such that:

1) $|\beta(k)| \leq 1$and$\beta(k) \in \mathcal{M}$,
2) $|\beta(m)| \leq q_m$and$\beta(m) \in \mathcal{K} \cup \phi$,
3) $\beta(k) = m$if and only if$k$is in$\beta(m)$,

where $\beta(k) = \{m\} \Leftrightarrow \beta(m) = \{k\}$ for $\forall m \in \mathcal{M}, \forall k \in \mathcal{K}$ and cardinality of matching result $\beta(.)$ is denoted by $|\beta(.)|$.

Through this definition, we represent our matching scheme as one-to-many matching. Condition 1 states that a UE can only be associated with one MVNO m reflecting (3a). In addition, an MVNO m can have multiple UEs to achieve the users' demands up to q_m (and condition 2). Here, q_m denotes the quota of MVNO m, which is the number of UEs an MVNO can support while guaranteeing their demand requirements. Additionally, when user k is not suitable for an MVNO, this may infringe constraint in (3c).

For the matching game, we define the preference profile for UE and MVNO that are the players of the game. The preference of UEs is made by the achievable data rate from an MVNO m, relating with (1). In the preference list of UEs, all MVNOs are ranked as descending order with the expected data rate. On the other hand, the preference profile for each MVNO is built for a set of UE that can maximize its profit and sum data rate, relating with (2). Through this preference profile, all UEs are ranked in descending order.

Once we build the matching scheme with the preference profile, the next aim is to design an algorithm that can obtain a stable solution. In matching theory, the stability notion is the main concept and the deferred-acceptance algorithm [41] is used mainly to obtain this notion. However, our game has variable quotas instead of static quota [11], thus the variable number of UEs can be accommodated over a slice due to variable demand. Therefore, the standard deferred-acceptance algorithm cannot be adopted for our problem. In our formulated game, the blocking pair is formally defined as:

A matching β is stable if there is no blocking pair (k, m), where $k \in \mathcal{K}$, $m \in \mathcal{M}$, such that $m \succ_k \beta(k)$ and $k \succ_m \beta(m)$. Here, current matched partners of user k and MVNO m are denoted by $\beta(k)$ and $\beta(m)$, respectively.

To resolve this blocking pair issue, we use the solution approach presented in [42]. However, this existing solution approach cannot be applied directly to our problem because of the difference in network dynamics. Therefore, we modified the solution to fit our problem. Moreover, our problem does not include externalities opposed to the problem presented in [42]. Before starting Algorithm 1, all MVNOs will get a slice which will include the random number of channels from each InPs. After multiple iterations of our algorithm, a slice has the optimal number of channels to cover the demands of the associated UEs. First, each UE and MVNO make their preference profile by using local information. Thereafter, each UE starts to propose to the first MVNO in the preference list for association based on its preference profile P_k^m at each iteration t. After receiving proposals, all MVNOs first calculate the channel requirement to generate a slice. If MVNO has enough available channels to achieve the required QoS, proposing UEs are accepted. In contrast, if MVNO does not have enough channels, MVNO denies the current accepted UEs that have lower priority than the proposing UE. In addition, the proposing UEs are also rejected if channels are still insufficient in the MVNO. Thereafter, all rejected UEs and MVNOs adjust the preference profiles. The remaining rejected UEs propose to the next preferred MVNOs in the updated preference list for association again.

This iterative procedure is complete when all UEs are accepted by MVNOs or there are no more MVNOs to propose. By using this process, the blocking pair is removed at each iteration [42], [43] and the algorithm converges to a stable solution. The result of the matching algorithm is a set of UEs that are associated with MVNOs given by the association vector $\boldsymbol{x}$. This matching game result is used as an input for the auction in the next phase.

After determining the set of UEs associated with MVNOs via matching game, the MVNOs need to obtain the resources from InPs. However, resources of InPs are limited and incur a certain cost. Therefore, an approach is required to determine which MVNOs are feasible to guarantee the revenue of InP. To overcome these challenges, we use an auction approach, as auction-based approaches drive competition among the MVNOs for obtaining resources. In other words, auction allows MVNOs to compete for the limited InP resource, where the MVNO who has the highest bidding value wins the auction, pays an optimal price, and gets the resource. In the following subsection, we present a detailed working of the auction based approach.

B. DISTRIBUTED AUCTION FOR WINNER AND PRICE DETERMINATION

As described in Fig. 3, in our auction model for resource allocation (AMRA) to MVNOs, we consider two players: (1) InPs as sellers of sliced resources and (2) multiple MVNOs as buyers.

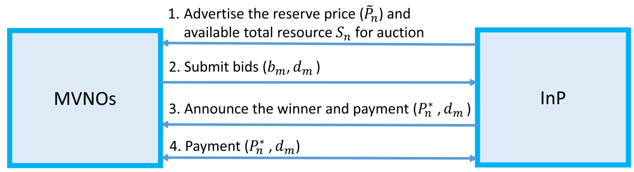

FIGURE 3. Auction model of each InP *n* for slice allocation to MVNOs.

InPs use AMRA to determine winning MVNOs and optimal prices that winning MVNOs have to pay for the slices allocated to them. Furthermore, we assume that all InPs are independent, and each InP n has its own network. In addition, we consider that each InP n has its own resources which can be divided and allocated to multiple MVNOs. This motivates us to use the auction model for divisible resources described in [26] and [44], as opposed to other auction mechanisms. Furthermore, we assume that we have multiple InPs, where n performs its own AMRA. In other words, there is no third-party auctioneer between the buyers (MVNOs) and sellers (InPs). An auctioneer ensures that the auction is conducted in a fair manner [45]; however, this causes the prices of resources to increase due to the charges that the seller must pay to the auctioneer. Therefore, to ensure that the AMRA is conducted in a fair manner, we prove that AMRA guarantees social welfare and individual rationality. In addition, we introduce a reservation unit price $\widetilde{P}_n$ in our auction model. Here, $\widetilde{P}_n$ is the minimum price that each InP n can accept per one unit of slice and S is the total amount of resources (i.e., the total number of slices). We consider $\widetilde{P}_n$ to be a minimum price that can help each InP n cover its CAPEX and OPEX. Therefore, selling resources below $\widetilde{P}_n$ can result in losses for the InP. However, if the InP n sets a high $\widetilde{P}_n$, the MVNOs will end up not buying the resources from InP n. This forces each InP n to study the market price and their competitors' strategies and set a reasonable $\widetilde{P}_n$. However, setting the value of $\widetilde{P}_n$ is considered to be beyond the scope of this paper and will be addressed in our future work.

The workflow of our AMRA is shown in Fig.3 and summarized as follows:

- *Step 1: In the first step, each InP n publicly announces the reservation price $\widetilde{P}_n$ and the slice size $\mathcal{S}_n$ (i.e., the number of channels available at an InP) for auction. This helps the MVNOs prepare and submit acceptable prices in their bids. In other words, each InP advertises its reservation price per one unit of slice s_n and the available resources to MVNOs.*
- *Step 2: Based on the received reservation price $\widetilde{P}_n$ and available sliced resources of each InP n, each MVNO $m \in \mathcal{M}$ chooses an InP to which it submits a bid for resources. Then, the MVNO prepares its bid (b_m, d_m) and submits it to the InP. In the bid, $b_m \geq \widetilde{P}_n$ is the unit price that each MVNO m is willing to pay for each one unit of slice (i.e., one channel) and d_m is the maximum amount of needed resources (the maximum slice size).*

- *Step 3: Each InP n collects all of the bids submitted by MVNOs and evaluates them. During the evaluation, for $b_m \geq \widetilde{P}_n$, the InP sorts the bids in descending order and allocates the resources starting with the highest bidding values. In other words, the InP allocates resources to the MVNOs who value the most. Then, the InP computes the payment P_n^* that each winning MVNO $m \in \mathcal{M}$ has to pay for the sliced resources allocated to him. The InP announces the winning MVNO(s) and the winning price(s).*
- *Step 4: Finally, each winning MVNO m pays P_n^* for the sliced resources allocated to him.*

Definition 1: In the AMRA, the MVNOs want to buy sliced resources from the InP, where $\widetilde{P}_n$ is the reservation price of one unit of slice from the InP. The MVNOs submit bids as demands, where(b_m, d_m) is the bid of each MVNO m. On receiving the bids from MVNOs, the InP chooses the bidding values that maximize its revenue and the social welfare of MVNOs.

In the AMRA, we consider that each MVNO m has its own valuation, denoted as $V_m(s_n)$ for slice s_n. Here, $V_m(s_n)$ can be expressed as follows:

$$V_m(s_n) = \begin{cases} v_m d_m, & \text{if MVNO } m \text{ participates in the AMRA,} \\ +\infty, & \text{otherwise.} \end{cases} \tag{4}$$

where v_m is the true valuation of MVNO m for slices s_n. However, when MVNO m does not participate in the AMRA, it is assigned a valuation of infinity. Furthermore, we consider (4) to be a private information of each MVNO. Therefore, in auction, each MVNO m submits b_m. We consider the slice $\mathcal{S}_n$ to be scarce, and we need a meaningful criterion for its allocation to MVNOs. One of the most important criteria is the efficiency, which is equivalent to the maximization of social welfare. Therefore, maximizing the revenue of the InP and the social welfare of MVNOs may be conflicting objectives. However, to overcome this issue, with $\widetilde{P}_n$, the AMRA ensures that the revenue of the InP do not become negative [26] and its revenue covers its CAPEX and OPEX. Therefore, based on $\widetilde{P}_n$, the valuation of the InP is given by:

$$V_n(\mathcal{S}_n) = \widetilde{P}_n \mathcal{S}_n \tag{5}$$

where $\mathcal{S}_n$ is the total amount of slices of InP n.

To achieve better efficiency, we apply the Vickrey-Clarke-Groves (VCG) mechanism. We choose the VCG mechanism because it allows welfare maximization and guarantees a truthful outcome [46]. VCG allows to implement auction without relying on prior knowledge regarding MVNOs valuations. In other words, the VCG enables competition and lets prices for resources to emerge from competition. Furthermore, as proved in [47], VCG is computationally feasible, i.e., polynomial time computable.

To apply the VCG, we define the maximum valuation $V_{\mathcal{M}}$ of all MVNOs with bidding values $b_m \geq \widetilde{P}_n$. The $V_{\mathcal{M}}$ is given by:

$$V_{\mathcal{M}} = \max_{b_m \geq \widetilde{P}_n} \sum_{m \in \mathcal{M}} b_m d_m \tag{6}$$

In the VCG, each MVNO m should pay for the damage it may cause on other MVNOs by participating in the AMRA. Therefore, we compute the total evaluation V_{-m} without each MVNO m, where V_{-m} is given by:

$$V_{-m} = \max_{b_{m'} \geq \widetilde{P}_n} \sum_{m' \in \mathcal{M} \setminus \{m\}} b_{m'} d_{m'} \tag{7}$$

From (6) and (7), we calculate the optimal price P_n^* for slice d_m that each winning MVNO m has to pay to the InP, which is given by:

$$P_n^* = V_{-m} - \sum_{m' \neq m} b_{m'} d_{m'}, \quad \forall \text{MVNO } m,\ m' \in \mathcal{M} \tag{8}$$

From equation (8), we define the MVNO's utility as follows:

Definition 2: For slice d_m, in which each MVNO's $m \in \mathcal{M}$ submits a bid (b_m, d_m), if MVNO $m \in \mathcal{M}$ wins the AMRA it pays P_n^* to InP n. Otherwise, MVNO $m \in \mathcal{M}$ pays nothing $(P_n^* = 0)$ if it loses the auction.

The utility U_m of any MVNO $m \in \mathcal{M}$ is given by:

$$U_m = y_{n,m}^{s_n} d_m (v_m - P_n^*), \quad \text{if MVNO } m \in \mathcal{W} \tag{9}$$

where $\mathcal{W} \subset \mathcal{M}$ is the set of winnners.

Definition 3: The AMRA is individually rational if and only if every MVNO $m \in \mathcal{M}$ has non-negative utility. Thus, $v_m \geq P_n^*$ and $U_m \geq 0$ for every MVNO $m \in \mathcal{M}$.

Remark 1: In the proposed AMRA, we use the individual rational definition in [48] to verify if AMRA satisfies the individual rationality of each bidder. The AMRA guarantees individual rationality; thus the AMRA sorts the bidding values in descending order and selects MVNOs $m \in \mathcal{M}$ that have the maximum bidding values as the winners, where each winner MVNOs $m \in \mathcal{W}$ pays P_n^*; this is contemplated a crucial payment $(P_n^* \geq \widetilde{P}_n)$ because of $b_m \geq \widetilde{P}_n$. Therefore, irrespective of the bidding values of other MVNOs, the bidders who value s_n most win the auction. The MVNOs who do not won the auction pays $P_n^* = 0$, while the winner pays $P_n^* \leq v_m$ payment, which assures that $U_m \geq 0$ (9). In other words, by participating in the AMRA, no MVNO has negative utility. In order to ensure that the AMRA guarantees an efficient or truthful outcome, the AMRA truthfulness is defined in Definition 4 and verified in Remark 2.

Definition 4: We consider the AMRA to be truthful if and only if every MVNO $m \in \mathcal{M}$ chooses to bid its true valuation $(b_m = v_m)$, i.e., rather than other possible bidding values $(b_m \neq v_m)$, i.e., by lying. The AMRA is truthful if it ensures that each MVNO's bidding value $(b_m = v_m)$ of MVNO $m \in \mathcal{M}$ for slice d_m maximizes the MVNO's utility over any other possible bidding values $(b_m \neq v_m)$ that deviate from its true valuation $(b_m = v_m)$.

Remark 2: To verify the truthfulness of the AMRA, we use the monotonicity and critical payment conditions

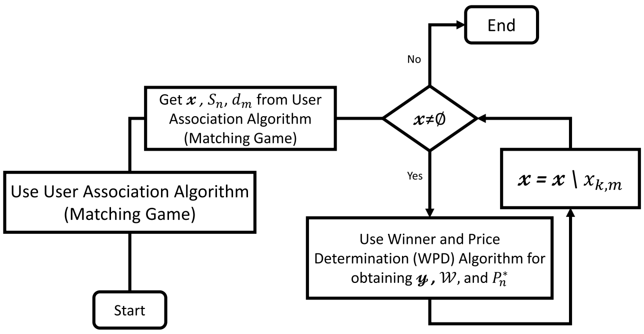

FIGURE 4. **Flowchart for joint solution.**

defined in [48] and [49]. To satisfy the monotonicity condition, we consider that each MVNO $m \in \mathcal{M}$ has two bidding values b'_m and b_m for slice d_m, where $b_m > b'_m$. The AMRA chooses MVNO $m \in \mathcal{M}$ as a winner, which has a bidding value that maximizes the total valuation. We sort the bidding values in descending order, if MVNO $m \in \mathcal{M}$ wins the AMRA using b'_m, where $b'_m < b_m$, MVNO $m \in \mathcal{M}$ will also win the AMRA by submitting b_m.

To satisfy the critical payment, each MVNO $m \in \mathcal{M}$ that has a bidding value which is higher than the bidding values of other MVNOs always wins the AMRA and pays P_n^* to the InP as an acceptable price that guarantees non-negative utility ($P_n^* \leq v_m$). Here, we consider $P_n^* \geq \widetilde{P}_n$ as a critical payment. Furthermore, for each MVNO $m \in \mathcal{M}$, using both monotonicity and the critical payment, sending a bidding value($b_m \neq v_m$) that diverge its true valuation ($v_m = b_m$) will not be helpful; consequently, the MVNO will not get any benefit by lying. To end this, the AMRA is truthful because it ensures that the truthful bidding ($b_m = v_m$) is the dominant strategy for every MVNO $m \in \mathcal{M}$.

C. MATCHING BASED AUCTION FOR JOINT SOLUTION

Here, we use the flowchart in Fig.4 to describe our joint solution, where matching game output $\boldsymbol{x}$ and some input of matching game such as, $\mathcal{S}_n$ and d_m are used as an input of auction between InPs and MVNOs for determining winning MVNOs $\mathcal{W}$ and the optimum prices P_n^* to pay to InP for assigned slices.

We use Algorithm 2 to determine the winning MVNOs and the optimal price P_n^* that the winning MVNOs should pay to the InP. We consider a set of bidders $\mathcal{M}$, vectors of bids b_m, reservation price $\widetilde{P}_n$, and total demand d_m for slice $\mathcal{S}_n$, as the inputs of Algorithm 2.

We initialize all variables at line 2, where $\boldsymbol{y} = \{y_{n,m}^{\mathcal{S}_n}\}$, $\forall m \in \mathcal{M}$ is a vector of binary decision variables. We consider all bids $b_m^* = \{b_m \geq \widetilde{P}_n\}$ as bids that cannot cause losses to the InP. Algorithm 2 starts with a winner determination process at line 5 by sorting bids in descending order and choosing the bidder $m \in \mathcal{M}$ that has the maximum bidding value as the winner. Then, at line 8, it computes the total valuation; adds bidder m (which has the maximum bidding value) as a winner to the winner set $\mathcal{W}$; and updates the set $\mathcal{M}$ of remaining bidders, in which the winner $m \in \mathcal{W}$

Algorithm 2 Matching Based Auction for Joint Solution

Input: $\mathcal{M}, \boldsymbol{x}, \widetilde{P}_n, b_m, d_m, |\mathcal{M}|$
1: ***Initialization***
2: $\mathcal{W} \leftarrow \emptyset$, $\mathcal{W}' \leftarrow \emptyset$, $\boldsymbol{y} \leftarrow (0, \ldots, 0)$, $P_n^* \leftarrow (0, \ldots, 0)$, $b_m^* \leftarrow (0, \ldots, 0)$, $V_{\mathcal{M}} \leftarrow (0, \ldots, 0)$, $V_{-m} \leftarrow (0, \ldots, 0)$, $V_{m'} \leftarrow (0, \ldots, 0)$
3: **while** $d_m \neq (0, \ldots, 0)$ and $b_m \geq \widetilde{P}_n$ **do**
4: $b_m^* \leftarrow b_m$
5: *Sort b_m^* in decreasing order*
6: ***repeat***
7: *Find MVNOs $m \in \mathcal{M}$ that has the maximum bid $max(b_m^*)$ as a winner*
8: $V_{\mathcal{M}} \leftarrow v_m + b_m d_m$
9: $\mathcal{W} \leftarrow \mathcal{W} \cup \{m\}$
10: $\mathcal{M} \leftarrow \mathcal{M} \backslash \{m\}$
11: $y_{n,m}^{\mathcal{S}_n} \leftarrow 1$
12: $\mathcal{S}_n = \mathcal{S}_n - d_m$
13: ***until*** $\mathcal{S}_n = \emptyset$ or $\mathcal{M} = \emptyset$
14: ***repeat***
15: *Find MVNO $m' \in \mathcal{M}' = \mathcal{M} \cup \mathcal{W} \backslash \{m\}$ that has the maximum bid $max(b_{m'}^*)$ when each MVNO $m \in \mathcal{W}$ is not participating in the auction*
16: $V_{-m} \leftarrow V_{-m} + b_{m'}$
17: $\mathcal{W}' \leftarrow \mathcal{W} \backslash \{m\}$
18: $\mathcal{S}_n = \mathcal{S}_n - d_{m'}$
19: ***until*** $\mathcal{S}_n = \emptyset$ or $\mathcal{W}' = \emptyset$
20: **for** *all $m' \in \mathcal{W} \backslash \{m\}$ (hint: $V_{m'} = \sum_{m' \neq m} b_{m'} d_{m'}$)* **do**
21: $V_{m'} \leftarrow V_{m'} + b_{m'}$
22: **end for**
23: $P_n^* \leftarrow V_{-m} - V_{m'}$
24: $P_n^* = P_n^* d_m$
25: **end while**
26: ***Return*** $\boldsymbol{y}, \mathcal{W}, P_n^*$
Output: $\boldsymbol{y}, \mathcal{W}, P_n^*$

is excluded from $\mathcal{M}$. The algorithm updates the vector of decision variables $\boldsymbol{y}$, and the same procedure continues from line 6 to line 13 until there are no more available slices $\mathcal{S}_n$ to be allocated to MVNOs or no more available bidders. In other words, in the AMRA, we can have multiple winning MVNOs, where resource allocation is based on the bidding values of bidders in descending order.

Thus, in the VCG, each MVNO m pays for the damage that may be caused to other MVNOs by participating in the AMRA. At line 20, the total valuation without each winner $m \in \mathcal{W}$ is calculated. Finally, Algorithm 2 computes the optimum price P_n^* that the winning MVNOs must pay to the

TABLE 2. Parameters for simulation [42].

Parameters	Value
Frequency of Carrier	2 GHZ
Structure of Frame	Type 1 (FDD)
Interval for Transmission Time (t)	1ms
Total transmitted power of BS	46 dBm
Bandwidth of Resource Block	180 kHz
Path loss model [50]	Free-space path loss model
Shadow fading	3 dB
Thermal noise (1 Hz at 20°C)	-174 dBm
Number of UEs ($\mathcal{K}$)	1:300
Range of User Demand	1∼15 bps/Hz
System Bandwidth for Comparison	1.4 MHz, 3 MHz, 5 MHz, 10 MHz
Weighting Parameter (ω)	0.5

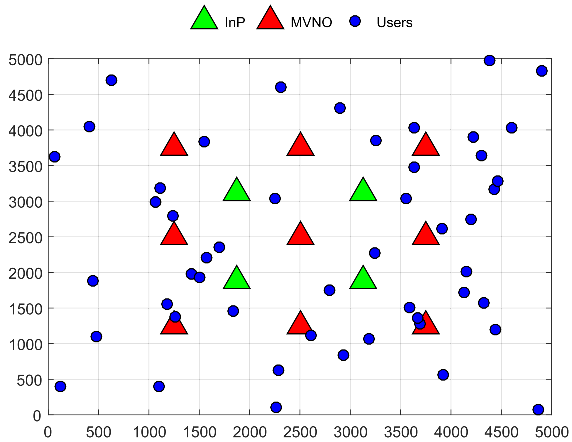

FIGURE 5. Simulation topology.

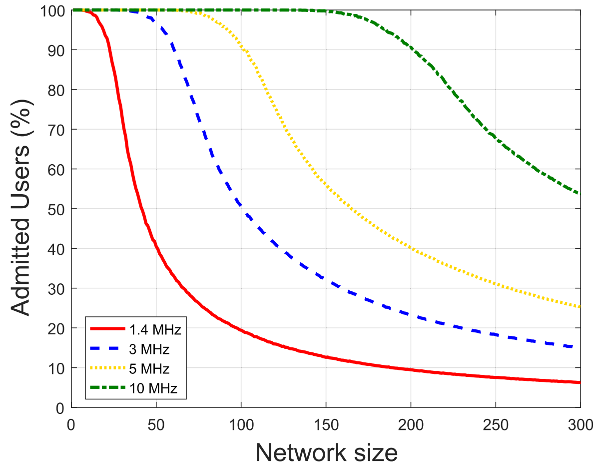

FIGURE 6. Admitted users for each system bandwidth.

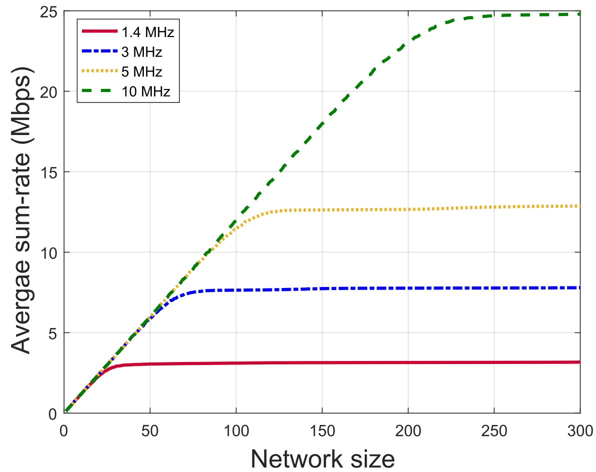

FIGURE 7. Average sum-data rate for each system bandwidth.

InP at line 24 and returns $\mathbf{y}$, $\mathcal{W}$, and P_n^* as the outputs at line 26.

IV. SIMULATION RESULTS AND ANALYSIS

In this section, we discuss the simulation results of the user association and matching based auction algorithms. Moreover, we provide the analysis of our proposed algorithms and comparisons with other approaches. Next, we present the simulation settings used to perform our simulations.

The entire network consists of multiple MVNOs and InPs, which a number of randomly located k UEs in a 5000 m × 5000 m coverage area. Moreover, we consider that the demand for user d_k is randomly distributed from 1 bps/Hz to 15 bps/Hz. In our simulations, we apply the free-space path loss model[2] and other important parameters used for the simulation setup are presented in Table 2.

A. MATCHING GAME RESULTS FOR USER ASSOCIATION

Fig. 5 shows the simulation topology, which has nine MVNOs and several UEs, for simulation of user association between MVNOs and UEs. Based on this environment, first, we conduct a simulation to verify the performance of the user association algorithm (Algorithm 1) under the various system bandwidths which has the different amount of resources, respectively. In Fig. 6, we show the user admission percentage vs. the network size (number of UEs) for different system bandwidth environments. The result indicates that when more available resources are available, more users can be accommodated in the system. When the number of users in the network is 100, approximately 20% of users can be admitted if the system bandwidth is 1.4 MHz. However, approximately 90% of users can be admitted if the system bandwidth is 5 MHz.

Fig. 7 shows that the average sum-rate of the network increases when we consider higher system bandwidth in each MVNO. When we consider the 10MHz as the system bandwidth, the result shows that the average sum-rate value is higher than other comparison environments because of the highest available amount of resources. This is reflected in Fig. 6 as well, each system bandwidth has a maximum number of users admitted, and as system bandwidth increases, the maximum number of the admitted user also

[2]We use the free-space path loss model for simulation as a channel model. The methodologies developed in this paper can also be applied to any type of channel model. The motivation for our choice is for the sake of simulation simplicity.

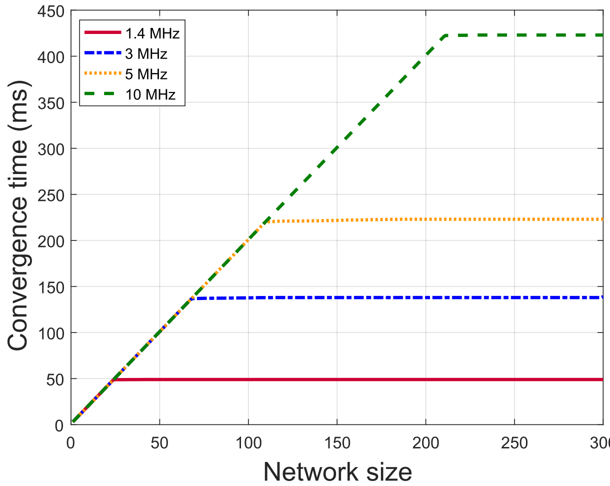

FIGURE 8. Convergence time for each system bandwidth.

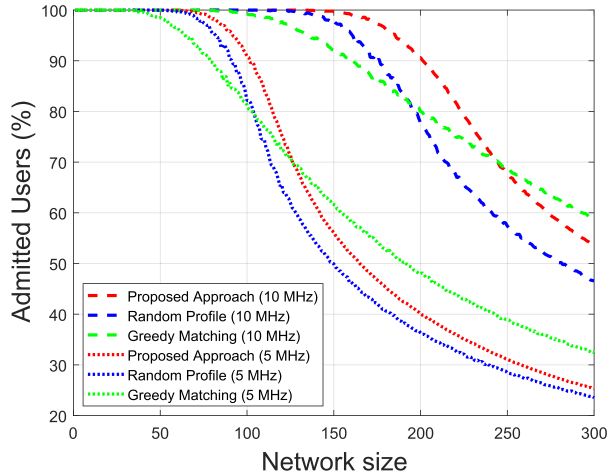

FIGURE 9. Comparison result of admitted users.

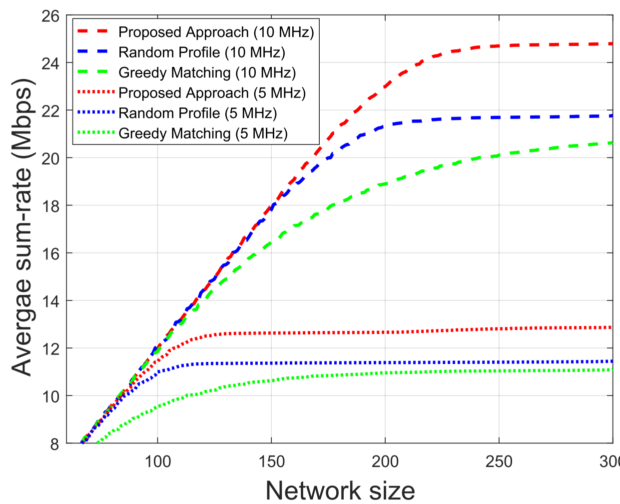

FIGURE 10. Comparison result average sum-rate.

increases. Thus, when the system bandwidth is increased, more user can be admitted into the network so that average sum-rate also increases. However, it saturates after a certain point as all network resources are exhausted and increase in the network size does not affect the average sum rate.

In Fig. 8, we study the convergence of Algorithm 1 for different network sizes. We increased the network size for different values for the bandwidth in order to observe convergence time. It can be seen that the convergence time increases with the system bandwidth. The reason for this increase is that higher bandwidth implies a larger number of resource blocks. Thus, more proposals are sent by the users until either acceptance or preference list exhaustion. This accept/reject process increases the required time for convergence especially at higher system bandwidth settings. Note that even for a high system bandwidth, the convergence time is less than 450 ms which is practically acceptable for a network setting of 250 or more UEs.

For the comparison result of user association, we select the random [51] preference profile approach and greedy matching approach [52] as baselines. In our proposed algorithm, the preference profile for each UE and MVNO is built via (1) and (2), respectively. After that, each preference profile is used as an efficient matching strategy to get a stable solution for the user association problem. Thus, based on the random preference profile approach, we analyze the effect of the preference profile in the matching algorithm for user association problem. In addition, our proposed algorithm is also compared with the greedy algorithm to analyze the efficiency from an algorithmic point of view.

Fig. 9 and Fig. 10 compare the proposed algorithm with the baselines. It can be seen that the proposed algorithm outperforms the baseline approaches [51], [52] in terms of increasing the number of admitted network users and improving resource utilization. As shown in Fig. 9, the result based on the random preference profile approach yields a worse performance compared to the proposed algorithm due to the randomly arranged profile used for the proposing strategy between MVNOs and users. When the number of users in the network is over 200 UEs, the random profile approach admits approximately 80% of the UEs, while the proposed method achieves 90%. Thus, the random profile approach has less resource utilization than the proposed algorithm. Hence, we deduce that the preference profile must also be considered optimally to find suitable matching in our network.

For the greedy algorithm, more users can be accommodated in a particular section than a random profile approach and proposed algorithm. However, as shown in Fig. 10, resource utilization becomes inefficient. In other words, the greedy approach accommodates a large number of users but does not efficiently use the resources of the entire network.

B. RESULTS OF MATCHING BASED AUCTION FOR RESOURCE ALLOCATION TO MVNOS

Based on the user association algorithm results between MVNOs and UEs, each MVNO decides the amount of slices that need to be allocated by InP n. In this subsection, we analyze the auction based resource allocation with

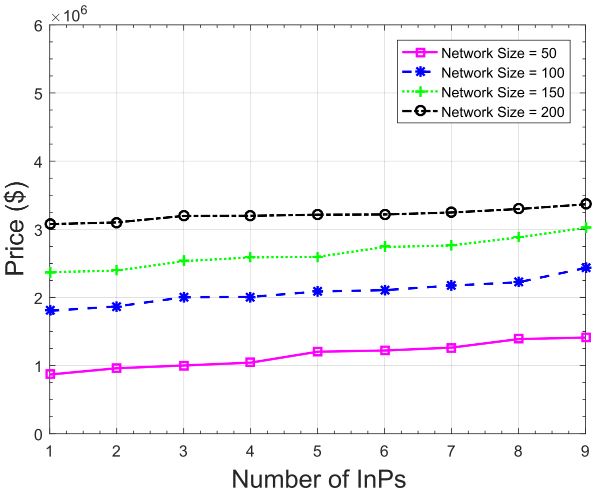

FIGURE 11. Optimal pricing offered by the InPs.

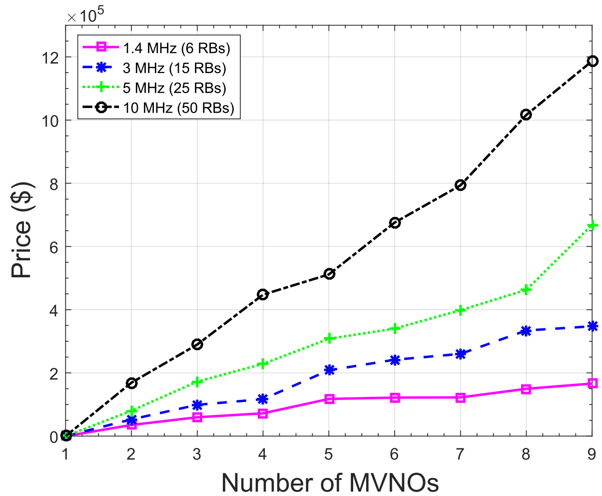

FIGURE 12. Sliced resource allocation to MVNOs and optimal pricing.

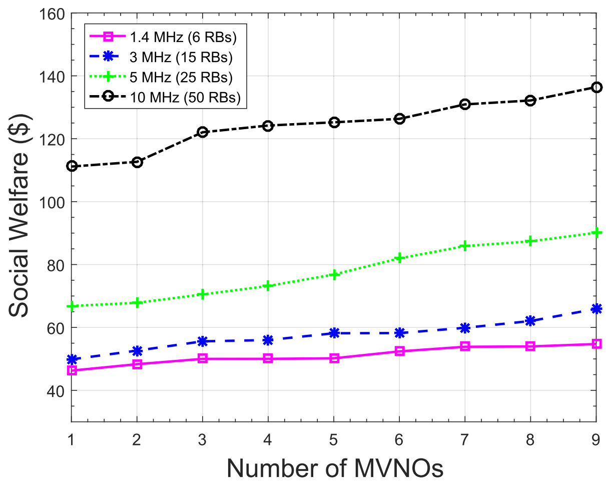

FIGURE 13. Social welfare maximization.

pricing results. In our auction model for resource allocation to MVNOs, we use multiple InPs as sellers of resources and multiple MVNOs as buyers. Each InP has the resources ranging from $s_n = 6$ to $s_n = 50$ resource blocks which will be allocated to multiple MVNOs. Furthermore, we use the reservation price[3] $\widetilde{P}_n = \$3$ and MVNO bidding values of $b_m = \$2$ to $b_m = \$8$. We assume that the InP announces the reservation price and the amount of available resources for the auction. Based on the available sliced resources for auction and the reservation price, each MVNO prepares and submits a bid to an InP. To determine the winning MVNO/bidder and optimal price, the InP uses the winner and price determination algorithm (Algorithm 2).

In Fig. 11, we increase the number of InPs from 1 to 9 for different network sizes to capture the pricing behavior of the network. From Fig. 11, we observe that the price increases both for network sizes and the number of InPs due to an increase in the competition among MVNOs for satisfying users' demands. In other words, an increase in the number of users increases the competition among MVNOs for obtaining resources from InPs via the auction. In turn, this behavior contributes to a price increase.

Fig. 12 shows the optimal prices that need to be paid by MVNOs to the InP for getting resources. This figure demonstrates that the optimal price P_n^* of each MVNO m for slices d_m rises when the number of bidders increases. In other words, the competition for obtaining resources arises when the number of MVNOs increases. In our auction, we use a VCG algorithm to obtain an efficient outcome, which becomes a dominant strategy for each MVNO and requires each MVNO to submit a bid that reports its valuation for the resource of InP, without knowing the bids of the other MVNOs. During the evaluation of all the bidding values submitted by MVNOs, each MVNO m should pay for the damage that its participation in the auction may cause to other MVNOs. In other words, the optimal price is a social cost, which is the difference between the optimal welfare of players other than $m \in \mathcal{W}$ when each player $m \in \mathcal{W}$ is not participating and the optimum welfare of the players other than $m \in \mathcal{W}$ from the chosen outcome when player $m \in \mathcal{W}$ is participating.

Fig. 13 shows the social welfare maximization, i.e., socially efficient allocation that maximizes the valuation of all bidders, as described in (6). Both Fig. 12 and Fig. 13 show that the optimal price and the social welfare increase as the number of bidders/MVNOs increase. In other words, when the number of MVNOs and sliced resources increase, the auction becomes more competitive, which results in an increase in the social welfare. Therefore, to maximize the welfare of all MVNOs, it is necessary to control the entire resource allocation, where the InP allocates resources until there are no more available resources to be allocated to MVNOs or no more available MVNOs that need resources.

As shown in Fig. 14, we compare the social welfare of our approach with other baselines. For the comparison, we use the well known approaches: random [51] and

[3]For pricing the resource, we use an arbitrary reservation price. However, any other pricing approach can also be used.

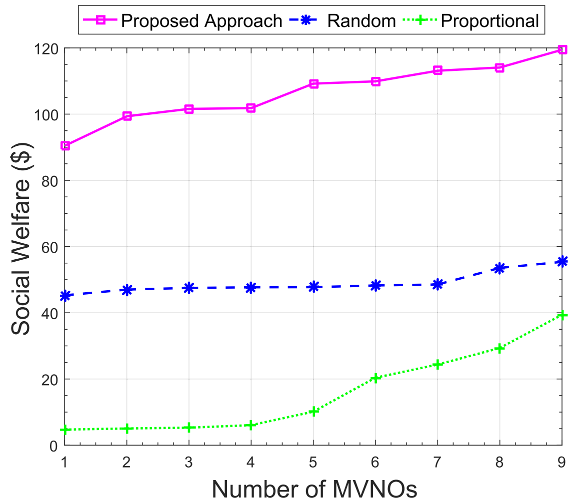

FIGURE 14. Comparison of our proposal with other existing approaches in terms of social welfare.

proportional [53]. We chose random and proportional as baseline approaches because they are easy to implement and practical in realistic systems such as 3G, 4G, and 5G cellular networks [54]–[56]. In random, we allocate slice resource randomly to each MVNOs based on its demand. Conversely, in proportion allocation, each MVNO receives a fraction of the slice resources based on its demand d_m, demands from other MVNOs $\sum_{m'} d_{m'}$, and available sliced resources $\mathcal{S}_n$ where the resource allocated to each MVNO $m \in \mathcal{M}$ equals to $\mathcal{S}_n \frac{d_m}{\sum_{m'} d_{m'}}$. After resource allocation, each MVNO has to pay for its allocated resources. Thus, our payment approach aims to maximize the social welfare of all the bidders, i.e., all MVNOs. In Fig. 14, The simulation results show that social welfare is non-decreasing by using different approaches. However, our approach has better performance as compared to random and proportional approaches because our auction-based approach allocates resources to MVNOs based on their bedding values in descending order, where the MNVO who has the highest bidding value wins the auction and gets the resource first. We consider that all MVNOs can obtain the resources needed in order to satisfy all users when the InP has enough resources and all MVNOs submitting the bidding values greater than or equals to the reservation price. In other words, all MVNOs win the auction. However, if we consider that the InP has limited resources and cannot satisfy the demands of all MNVOs, i.e., some MVNOs win the auction and obtain resources to satisfy their users while other MVNOs loss the auction. Therefore, based on available resources of InP, Fig. 15 shows the total number of users and the number of unallocated users, where the unallocated users are the users associated with the MVNOs that loss the auction. From this figure, we can see that when the InP has a high amount of resources such as $R = 50$, we have the small number of unallocated users, i.e., we have a large number of allocated users (in other words, more MVNOs can win the auction).

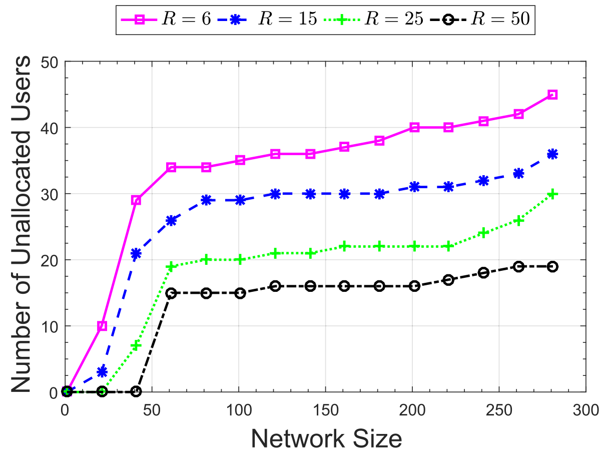

FIGURE 15. Illustration of the network size and the number of unallocated users.

V. CONCLUSION

In this paper, we have proposed a virtualized resource allocation method by using distributed approaches in a wireless network virtualization environment. In the system model, we have considered multiple InPs and MVNOs for resource assignment based on an optimal pricing scenario. First, a matching algorithm is used to solve the user association problem; this is based on the preference profile of each user and MVNO. Using the results of user association, each MVNO decides a bidding value to get resources that meet the demands of its associated users. InPs check the reservation price, which is a minimum price related to their OPEX and CAPEX. After the reservation price is determined, InPs advertise this price and the amount of resources available for auction to all MVNOs. Based on the reservation price, bidding value, and available resources, our proposed algorithm finds the optimal price and allocates resources accordingly. Our simulation results show that the proposed distributed approaches are stable and can be easily implemented into environments that consider multiple winners (MVNOs) and InPs. Future work can extend our approach by incorporating machine learning techniques such as those in [57], [58].

REFERENCES

[1] C. Liang and F. R. Yu, "Wireless network virtualization: A survey, some research issues and challenges," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 358–380, 1st Quart., 2015.
[2] W. Saad, M. Bennis, and M. Chen, "A vision of 6G wireless systems: Applications, trends, technologies, and open research problems," *IEEE Netw.*, early access, Oct. 15, 2019, doi: 10.1109/MNET.001.1900287.
[3] U. Habiba and E. Hossain, "Auction mechanisms for virtualization in 5G cellular networks: Basics, trends, and open challenges," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 3, pp. 2264–2293, 3rd Quart., 2018.
[4] S. Kazmi, L. Khan, N. Tran, and C. Hong, *Network Slicing for 5G and Beyond Networks*. Cham, Switzerland: Springer, 2019.
[5] M. Vincenzi, A. Antonopoulos, E. Kartsakli, J. Vardakas, L. Alonso, and C. Verikoukis, "Multi-tenant slicing for spectrum management on the road to 5G," *IEEE Wireless Commun.*, vol. 24, no. 5, pp. 118–125, Oct. 2017.
[6] O. Al-Khatib, W. Hardjawana, and B. Vucetic, "Spectrum sharing in multi-tenant 5G cellular networks: Modeling and planning," *IEEE Access*, vol. 7, pp. 1602–1616, Jan. 2019.
[7] G. Zhang, K. Yang, J. Wei, K. Xu, and P. Liu, "Virtual resource allocation for wireless virtualization networks using market equilibrium theory," in *Proc. IEEE Conf. Comput. Commun. Workshops (INFOCOM WKSHPS)*, Apr./May 2015, pp. 366–371.

[8] J. Wei, K. Yang, G. Zhang, and Z. Hu, "Pricing-based power allocation in wireless network virtualization: A game approach," in *Proc. Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, Dubrovnik, Croatia, Aug. 2015.
[9] S. M. A. Kazmi and C. S. Hong, "A matching game approach for resource allocation in wireless network virtualization," in *Proc. 11th Int. Conf. Ubiquitous Inf. Manage. Commun. (IMCOM)*, Beppu, Japan, 2017, pp. 1–6.
[10] T. M. Ho, N. H. Tran, S. M. A. Kazmi, and C. S. Hong, "Dynamic pricing for resource allocation in wireless network virtualization: A Stackelberg game approach," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Da Nang, Vietnam, Jan. 2017, pp. 429–434.
[11] S. M. A. Kazmi, N. Tran, W. Saad, L. B. Le, T. M. Ho, and C. S. Hong, "Optimized resource management in heterogeneous wireless networks," *IEEE Commun. Lett.*, vol. 20, no. 7, pp. 1397–1400, Jul. 2016.
[12] M. Touati, R. El-Azouzi, M. Coupechoux, E. Altman, and J.-M. Kelif, "A controlled matching game for WLANs," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 3, pp. 707–720, Mar. 2017.
[13] T. Sanguanpuak, S. Guruacharya, N. Rajatheva, M. Bennis, and M. Latva-Aho, "Multi-operator spectrum sharing for small cell networks: A matching game perspective," *IEEE Trans. Wireless Commun.*, vol. 16, no. 6, pp. 3761–3774, Jun. 2017.
[14] M. Zeng, S. Leng, Y. Zhang, and J. He, "QoE-aware power management in vehicle-to-grid networks: A matching-theoretic approach," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 2468–2477, Jul. 2018.
[15] Y. Gu, W. Saad, M. Bennis, M. Debbah, and Z. Han, "Matching theory for future wireless networks: Fundamentals and applications," *IEEE Commun. Mag.*, vol. 53, no. 5, pp. 52–59, May 2015.
[16] O. Semiari, W. Saad, and M. Bennis, "Joint millimeter wave and microwave resources allocation in cellular networks with dual-mode base stations," *IEEE Trans. Wireless Commun.*, vol. 16, no. 7, pp. 4802–4816, Jul. 2017.
[17] O. Semiari, W. Saad, M. Bennis, and B. Maham, "Caching meets millimeter wave communications for enhanced mobility management in 5G networks," *IEEE Trans. Wireless Commun.*, vol. 17, no. 2, pp. 779–793, Feb. 2018.
[18] O. Semiari, W. Saad, S. Valentin, M. Bennis, and H. V. Poor, "Context-aware small cell networks: How social metrics improve wireless resource allocation," *IEEE Trans. Wireless Commun.*, vol. 14, no. 11, pp. 5927–5940, Nov. 2015.
[19] E. Datsika, A. Antonopoulos, D. Yuan, and C. Verikoukis, "Matching theory for over-the-top service provision in 5G networks," *IEEE Trans. Wireless Commun.*, vol. 17, no. 8, pp. 5452–5464, Aug. 2018.
[20] E. Datsika, A. Antonopoulos, N. Zorba, and C. Verikoukis, "Matching game based virtualization in shared LTE-A networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2016, pp. 1–6.
[21] D. H. Kim, S. M. A. Kazmi, and C. S. Hong, "Cooperative slice allocation for virtualized wireless network: A matching game approach," in *Proc. IEEE Int. Conf. Ubiquitous Inf. Manage. Commun. (IMCOM)*, Langkawi, Malaysia, Jan. 2018, pp. 1–6.
[22] D. H. Kim, A. Ndikumana, S. M. A. Kazmi, K. Kim, M. S. Munir, W. Saad, and C. S. Hong, "Pricing mechanism for virtualized heterogeneous resources in wireless network virtualization," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Barcelona, Spain, Jan. 2020, pp. 366–371.
[23] Y. Zhang, C. Lee, D. Niyato, and P. Wang, "Auction approaches for resource allocation in wireless systems: A survey," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1020–1041, 3rd Quart., 2013.
[24] B. Cao, W. Lang, Y. Li, Z. Chen, and H. Wang, "Power allocation in wireless network virtualization with Buyer/Seller and auction game," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, San Diego, CA, USA, Dec. 2015, pp. 1–7.
[25] L. Gao, P. Li, Z. Pan, N. Liu, and X. You, "Virtualization framework and VCG based resource block allocation scheme for LTE virtualization," in *Proc. IEEE 83rd Veh. Technol. Conf. (VTC Spring)*, Nanjing, China, May 2016, pp. 1–6.
[26] I. Koutsopoulos and G. Iosifidis, "Auction mechanisms for network resource allocation," in *Proc. Int. Symp. Modeling Optimization Mobile, Ad Hoc, Wireless Netw. (WiOpt)*, Avignon, France, May 2010, pp. 554–563.
[27] L. Liang, Y. Wu, G. Feng, X. Jian, and Y. Jia, "Online auction-based resource allocation for service-oriented network slicing," *IEEE Trans. Veh. Technol.*, vol. 68, no. 8, pp. 8063–8074, Aug. 2019.
[28] W. Borjigin, K. Ota, and M. Dong, "In broker we trust: A double-auction approach for resource allocation in NFV markets," *IEEE Trans. Netw. Service Manage.*, vol. 15, no. 4, pp. 1322–1333, Dec. 2018.
[29] X. Liu, Q. Qiu, and L. Lv, "An online combinatorial auction based resource allocation and pricing mechanism for network slicing in 5G," in *Proc. IEEE 19th Int. Conf. Commun. Technol. (ICCT)*, Xi'an, China, Oct. 2019, pp. 908–913.
[30] N. Tadayon and S. Aissa, "Radio resource allocation and pricing: Auction-based design and applications," *IEEE Trans. Signal Process.*, vol. 66, no. 20, pp. 5240–5254, Oct. 2018.
[31] M. Oikonomakou, A. Antonopoulos, L. Alonso, and C. Verikoukis, "Energy sharing and trading in multi-operator heterogeneous network deployments," *IEEE Trans. Veh. Technol.*, vol. 68, no. 5, pp. 4975–4988, May 2019.
[32] P. Belzarena, A. Ferragut, and F. Paganini, "Network bandwidth allocation via distributed auctions with time reservations," in *Proc. 28th Int. Conf. Comput. Commun. (INFOCOM)*, Apr. 2009, pp. 2816–2820.
[33] D. C. Parkes and J. Shneidman, "Distributed implementations of Vickrey-clarke-groves mechanisms," in *Proc. 3rd Int. Joint Conf. Auton. Agents Multiagent Syst.*, Jul. 2004, pp. 261–268.
[34] H. Halabian, "Distributed resource allocation optimization in 5G virtualized networks," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 3, pp. 627–642, Mar. 2019.
[35] F. Zhang, X. Zhou, and M. Sun, "On-demand receiver-centric channel allocation via constrained VCG auction for spatial spectrum reuse," *IEEE Syst. J.*, vol. 13, no. 3, pp. 2519–2530, Sep. 2019.
[36] K. Zhu and E. Hossain, "Virtualization of 5G cellular networks as a hierarchical combinatorial auction," *IEEE Trans. Mobile Comput.*, vol. 15, no. 10, pp. 2640–2654, Oct. 2016.
[37] X. Zhang, H. Qian, K. Zhu, R. Wang, and Y. Zhang, "Virtualization of 5G cellular networks: A combinatorial double auction approach," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Singapore, Dec. 2017, pp. 1–6.
[38] K. Zhu, Z. Cheng, B. Chen, and R. Wang, "Wireless virtualization as a hierarchical combinatorial auction: An illustrative example," in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, San Francisco, CA, USA, Mar. 2017, pp. 1–6.
[39] H. Zhao, K. Ding, N. I. Sarkar, J. Wei, and J. Xiong, "A simple distributed channel allocation algorithm for D2D communication pairs," *IEEE Trans. Veh. Technol.*, vol. 67, no. 11, pp. 10960–10969, Nov. 2018.
[40] H. Hawilo, L. Liao, A. Shami, and V. C. M. Leung, "NFV/SDN-based vEPC solution in hybrid clouds," in *Proc. IEEE Middle East North Afr. Commun. Conf. (MENACOMM)*, Jounieh, Lebanon, Apr. 2018, pp. 1–6.
[41] A. E. Roth, "Deferred acceptance algorithms: History, theory, practice, and open questions," *Int. J. Game Theory*, vol. 36, nos. 3–4, pp. 537–569, Mar. 2008.
[42] S. M. A. Kazmi, N. H. Tran, W. Saad, Z. Han, T. M. Ho, T. Z. Oo, and C. S. Hong, "Mode selection and resource allocation in device-to-device communications: A matching game approach," *IEEE Trans. Mobile Comput.*, vol. 16, no. 11, pp. 3126–3141, Nov. 2017.
[43] S. M. A. Kazmi, N. H. Tran, T. M. Ho, T. Z. Oo, T. LeAnh, S. Moon, and C. S. Hong, "Resource management in dense heterogeneous networks," in *Proc. 17th Asia–Pacific Netw. Oper. Manage. Symp. (APNOMS)*, Busan, South Korea, Aug. 2015, pp. 440–443.
[44] S. Zou, Z. Ma, and X. Liu, "Auction-based mechanism for dynamic and efficient resource allocation," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 48, no. 1, pp. 34–49, Jan. 2018.
[45] N. C. Luong, D. T. Hoang, P. Wang, D. Niyato, and Z. Han, "Applications of economic and pricing models for wireless network security: A survey," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 4, pp. 2735–2767, Jul. 2017.
[46] M. B. Caminati, M. Kerber, C. Lange, and C. Rowat, "VCG-combinatorial Vickrey-clarke-groves auctions," *Arch. Formal Proofs*, vol. 2015, 2015.
[47] N. Nisan and A. Ronen, "Computationally feasible VCG mechanisms," *J. Artif. Intell. Res.*, vol. 29, pp. 19–47, May 2007.
[48] L. Blumrosen and N. Nisan, "Combinatorial auctions," in *Algorithmic Game Theory*. New York, NY, USA: Cambridge Univ. Press, 2007, pp. 267–300.
[49] A. Ndikumana, N. H. Tran, T. M. Ho, D. Niyato, Z. Han, and C. S. Hong, "Joint incentive mechanism for paid content caching and price based cache replacement policy in named data networking," *IEEE Access*, vol. 6, pp. 33702–33717, 2018.
[50] S. Choudhary and D. K. Dhaka, "Path loss prediction models for wireless communication channels and its comparative analysis," *Int. J. Eng., Manage. Sci.*, vol. 2, no. 3, pp. 38–43, Mar. 2015.
[51] E. Budish, Y.-K. Che, F. Kojima, and P. Milgrom, "Designing random allocation mechanisms: Theory and applications," *Amer. Econ. Rev.*, vol. 103, no. 2, pp. 585–623, Apr. 2013.

[52] J. Liu, C.-C. Zhao, and Z.-G. Ren, "The application of greedy algorithm in real life," in *Proc. Int. Conf. Manuf. Construct. Energy Eng. (MCEE)*, Hong Kong, Aug. 2016, pp. 1–7.

[53] T. Nguyen and M. Vojnovic, "Weighted proportional allocation," *ACM SIGMETRICS Perform. Eval. Rev.*, vol. 39, no. 1, pp. 133–144, Jun. 2011.

[54] A. Ndikumana, N. H. Tran, T. M. Ho, Z. Han, W. Saad, D. Niyato, and C. S. Hong, "Joint communication, computation, caching, and control in big data multi-access edge computing," *IEEE Trans. Mobile Comput.*, early access, Mar. 29, 2019, doi: 10.1109/TMC.2019.2908403.

[55] X. Liu, Z. Qin, Y. Gao, and J. A. McCann, "Resource allocation in wireless powered IoT networks," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4935–4945, Jun. 2019.

[56] S. M. A. Kazmi, T. N. Dang, I. Yaqoob, A. Ndikumana, E. Ahmed, R. Hussain, and C. S. Hong, "Infotainment enabled smart cars: A joint communication, caching, and computation approach," *IEEE Trans. Veh. Technol.*, vol. 68, no. 9, pp. 8408–8420, Sep. 2019.

[57] M. Chen, Z. Yang, W. Saad, C. Yin, H. V. Poor, and S. Cui, "A joint learning and communications framework for federated learning over wireless networks," 2019, *arXiv:1909.07972*. [Online]. Available: http://arxiv.org/abs/1909.07972

[58] A. Ferdowsi and W. Saad, "Brainstorming generative adversarial networks (BGANs): Towards multi-agent generative models with distributed private datasets," 2020, *arXiv:2002.00306*. [Online]. Available: http://arxiv.org/abs/2002.00306

DO HYEON KIM received the B.S. degree in communication engineering from Jeju National University, in 2014, and the M.S. degree from Kyung Hee University, in 2017, where he is currently pursuing the Ph.D. degree with the Department of Computer Science and Engineering. His research interests include multiaccess edge computing and wireless network virtualization.

S. M. AHSAN KAZMI received the master's degree in communication system engineering from the National University of Scvaiences and Technology (NUST), Pakistan, in 2012, and the Ph.D. degree in computer science and engineering from Kyung Hee University, South Korea, in 2017. Since 2018, he has been with the Institute of Information Systems (IIS), Innopolis University, Innopolis, Tatarstan, Russia, where he is currently an Assistant Professor. His research interests include applying analytical techniques of optimization and game theory to radio resource management for future cellular networks. He received the Best KHU Thesis Award in engineering, in 2017, and several best paper awards from prestigious conferences.

ANSELME NDIKUMANA received the B.S. degree in computer science from the National University of Rwanda, in 2007, and the Ph.D. degree in computer engineering from Kyung Hee University, South Korea, in August 2019. Since September 2019, he has been with the Faculty of Computing and Information Sciences, University of Lay Adventists of Kigali, Rwanda, where he is currently a Lecturer. His professional experiences include a Chief Information System, a System Analyst, and a Database Administrator at Rwanda Utilities Regulatory Authority, from 2008 to 2014. His research interests include deep learning, multiaccess edge computing, information centric networking, and in-network caching.

AUNAS MANZOOR received the M.S. degree in electrical engineering with a specialization in telecommunication from the National University of Science and Technology, Pakistan, in 2015. He is currently pursuing the Ph.D. degree with the Department of Computer Science and Engineering, Kyung Hee University, South Korea. His research interests include applying analytical techniques for resource management in mobile cellular networks.

WALID SAAD (Fellow, IEEE) received the Ph.D. degree from the University of Oslo, in 2010. He is currently a Professor with the Department of Electrical and Computer Engineering, Virginia Tech, where he leads the Network sciEnce, Wireless, and Security (NEWS) Laboratory. His research interests include wireless networks, machine learning, game theory, security, unmanned aerial vehicles, cyber-physical systems, and network science. He is a Fellow of an IEEE Distinguished Lecturer. He was a recipient of the NSF CAREER Award, in 2013, the AFOSR Summer Faculty Fellowship, in 2014, and the Young Investigator Award from the Office of Naval Research (ONR), in 2015. He was the author/coauthor of eight conference best paper awards at WiOpt in 2009, ICIMP, in 2010, IEEE WCNC, in 2012, IEEE PIMRC, in 2015, IEEE SmartGridComm, in 2015, EuCNC, in 2017, IEEE GLOBECOM, in 2018, and IFIP NTMS, in 2019. He was a recipient of the 2015 Fred W. Ellersick Prize from the IEEE Communications Society, the 2017 IEEE ComSoc Best Young Professional in Academia Award, and the 2018 IEEE ComSoc Radio Communications Committee Early Achievement Award. From 2015 to 2017, he was named the Stephen O. Lane Junior Faculty Fellow at Virginia Tech and, in 2017, he was named the College of Engineering Faculty Fellow. He received the Dean's Award for Research Excellence from Virginia Tech, in 2019. He currently serves as an Editor for the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, the IEEE TRANSACTIONS ON MOBILE COMPUTING, the IEEE TRANSACTIONS ON COGNITIVE COMMUNICATIONS AND NETWORKING, and the IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY. He is also an Editor-at-Large for the IEEE TRANSACTIONS ON COMMUNICATIONS.

CHOONG SEON HONG (Senior Member, IEEE) received the B.S. and M.S. degrees in electronic engineering from Kyung Hee University, Seoul, South Korea, in 1983 and 1985, respectively, and the Ph.D. degree from Keio University, Japan, in 1997. In 1988, he joined KT, where he was involved in broadband networks as a Member of Technical Staff. Since 1993, he has been with Keio University. He was with the Telecommunications Network Laboratory, KT, as a Senior Member of Technical Staff and the Director of the Networking Research Team, until 1999. Since 1999, he has been a Professor with the Department of Computer Science and Engineering, Kyung Hee University. His research interests include the future Internet, ad hoc networks, network management, and network security. He has served as the General Chair, the TPC Chair/Member, or an Organizing Committee Member for international conferences, such as NOMS, IM, APNOMS, E2EMON, CCNC, ADSN, ICPP, DIM, WISA, BcN, TINA, SAINT, and ICOIN. He was an Associate Editor of the IEEE TRANSACTIONS ON NETWORK AND SERVICE MANAGEMENT and the *Journal of Communications and Networks*. He is currently serving as an Associate Editor for the *International Journal of Network Management* and *Future Internet* Journal and an Associate Technical Editor of the *IEEE Communications Magazine*. He is a member of ACM, IEICE, IPSJ, KIISE, KICS, KIPS, and OSIA