Enabling Radio-as-a-Service With Truthful Auction Mechanisms

Jing Wang, *Student Member, IEEE*, Dejun Yang, *Member, IEEE*, Jian Tang, *Senior Member, IEEE*, and Mustafa Cenk Gursoy, *Senior Member, IEEE*

***Abstract*— We envision that in the near future, just as Infrastructure-as-a-Service, radios, and radio resources in a wireless network can also be provisioned as a service to mobile virtual network operators (MVNOs), which we refer to as *Radio-as-a-Service (RaaS)*. A major obstacle for wide adoption of RaaS is the lack of incentives and fairness for allocating radio resources among MVNOs. In this paper, we present a novel auction-based model to enable fair pricing and fair resource allocation according to real-time needs of MVNOs for RaaS. Based on the proposed model, we study the auction mechanism design with the objective of maximizing social welfare. First, we present an integer linear programming and Vickrey–Clarke–Groves-based auction mechanism for obtaining optimal social welfare. To reduce time complexity, we present a polynomial-time greedy mechanism for the RaaS auction. Both methods have been formally shown to be truthful and individually rational. Extensive simulation results show that the proposed greedy auction mechanism can quickly produce close-to-optimal solutions. Furthermore, to prevent winning bidders from making 0 payment, we introduce reserve prices, and present auction mechanisms with reserve prices, which are shown to be truthful and individually rational too.**

***Index Terms*— Wireless networking, mobile cloud computing, radio-as-a-service (RaaS), auction mechanism, truthfulness, pricing and resource allocation.**

I. Introduction

VIRTUALIZATION, inspired by the success of application of Virtual Machines (VMs) in cloud computing, has been introduced to wireless networking recently [9], enabling support for multiple Mobile Virtual Network Operators (MVNOs) via isolated slices over a shared wireless substrate.

We envision that in the near future, just as Infrastructure-as-a-Service (IaaS), radios and radio resources in a wireless network can also be provisioned as a service to multiple MVNOs, which we refer to as *Radio-as-a-Service (RaaS)*. In an RaaS cloud, Base Stations (BSs) are operated by the cloud service provider, which can lease radio resources of BSs to MVNOs for profit. For an MVNO, similar to a tenant in an IaaS cloud, it pays the cloud service provider to use radio resources to serve its own users. Usually, multiple MVNOs share common radio resources in an RaaS cloud. For wide adoption of RaaS, on one hand, the cloud service provider needs to be able to collect a fair amount of payment from each MVNO for radio resources it leases; on the other hand, an MVNO needs to be able to obtain sufficient resources from the cloud service provider to well serve its users at a fair cost. In an IaaS cloud (such as Amazon EC2), resources are given to tenants in the format of VM and storage space, which has guaranteed capabilities/capacities for computing and storage respectively. However, in an RaaS, bandwidth (i.e., transmission capability) of a wireless link is time-varying. An MVNO, which rents a certain amount of radio resources beforehand, may not have sufficient bandwidth for its users in certain periods of time. Hence, supporting RaaS is a very challenging task but has not yet been well studied. A major obstacle for the wide adoption of RaaS is the lack of incentives and fairness for allocating radio resources among MVNOs.

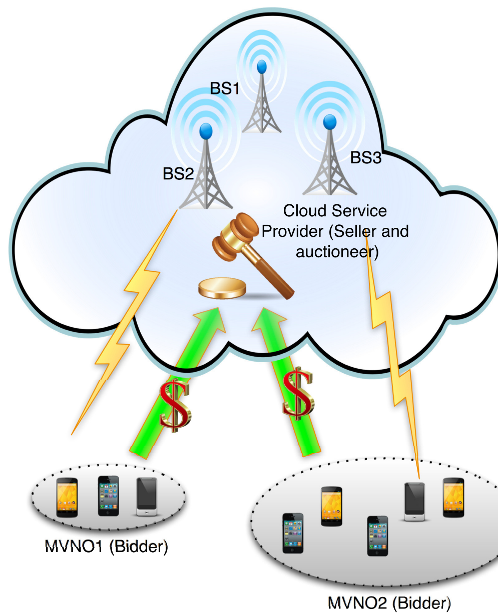


Fig. 1. The RaaS auction.

In this paper, we introduce a novel auction-based model to achieve the goal of enabling fair pricing and reasonable resource allocation for RaaS. In our model as illustrated in Fig. 1, cloud service provider (i.e., seller) sells its radio

Manuscript received May 10, 2016; revised November 23, 2016; accepted January 21, 2017. Date of publication March 13, 2017; date of current version April 7, 2017. This work was supported by NSF under Grant 1443966. A short version of this paper was presented in the IEEE ICC, June 2015 [20]. The associate editor coordinating the review of this paper and approving it for publication was M. Li. *(Corresponding author: Mustafa Cenk Gursoy.)*

J. Wang, J. Tang, and M. C. Gursoy are with the Department of Electrical Engineering and Computer Science, Syracuse University, Syracuse, NY 13244 USA (e-mail: jwang93@syr.edu; jtang02@syr.edu; mcgursoy@syr.edu).

D. Yang is with the Department of Electrical Engineering and Computer Science, Colorado School of Mines, Golden, CO 80401 USA (e-mail: djyang@mines.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TWC.2017.2663430

resources to MVNOs. MVNOs (i.e., bidders or buyers) participate in the auction, bid the resources according to their real-time needs and make payment to the cloud service provider. Moreover, the cloud service provider plays the role of auctioneer so that it will determine the winners among MVNOs and clear prices MVNOs should pay.

To support RaaS, we allow each MVNO to bid for a combination of demanded resources on each BS. This auction can be related to a *combinatorial auction* [15], with the difference lying in the fact that the demanded resources could be only a fraction of the available resources on each BS. So its resources are actually shared among multiple MVNOs. While in a conventional combinatorial auction, a bidder expresses its valuation of a combination of items, and the auction does not allow item sharing.

Auction mechanism design is crucial for supporting RaaS, because it directly determines the trading rules between the seller (cloud service provider) and bidders (MVNOs); furthermore, it implicitly defines the behaviors of bidders. Specifically, *truthfulness* (a.k.a incentive capability or strategy-proofness) [15] and *individual rationality* [11] are highly desirable in RaaS auction mechanisms. An auction mechanism is truthful if a bidder will not increase its payoff by making any other bid instead of the true value. Revealing the true private value is every participating bidders dominant strategy no matter what strategies other bidders are doing [22]. An auction lacking truthfulness could be vulnerable to market manipulation and produce very poor outcomes [8]. In addition, an auction mechanism is individually rational if the payoff of every bidder is non-negative.

A. Summary of Key Contributions

To the best of our knowledge, we are the first to develop an auction-based model and auction mechanisms with provably-good properties for RaaS. We summarize our contributions of this paper in the following:

- We formally define the RaaS auction mechanism design problem with the objective of maximizing social welfare.
- We present an Integer Linear Programming (ILP) and Vickrey-Clarke-Groves (VCG) based auction mechanism for obtaining optimal social welfare. To reduce time complexity, we present a polynomial-time greedy auction mechanism. Moreover, we show that the proposed mechanisms are both truthful and individually rational.
- To prevent winning bidders from making 0 payment, we introduce reserve prices and present auction mechanisms with reserve prices, which are shown to be both truthful and individually rational too.
- We present extensive simulation results to show the proposed greedy mechanism achieves significant running time savings and produces close-to-optimal solutions. Moreover, we justify effectiveness of the proposed auction mechanisms with reserve prices via simulation results.

B. Paper Organization

The remainder of this paper is organized as follows. We review existing related work in Section II. We present system model and auction formulation with necessary preliminaries in Section III. In Section IV, We present an ILP and VCG based auction mechanism to obtain optimal social welfare. Then, we present a heuristic auction mechanism with polynomial time complexity in Section V. In Section VI, we present auction mechanisms with reserve prices. In Section VII, we present extensive simulation results to justify the proposed auction mechanisms. We conclude this paper in Section VIII.

II. Related Work

Cloud-based wireless networking and wireless virtualization have been studied recently. In [3], the framework CloudIQ was proposed to partition BSs into groups that are simultaneously processed on a shared homogeneous compute platform, and to schedule BSs to meet real-time processing requirements. A similar cloud-based wireless system, FluidNet, was introduced in [18]. Cudipati *et al.* [6] introduced SoftRAN, a software defined centralized control plane for RANs that abstracts all BSs in a local geographical area as a virtual big BS. Kokku *et al.* [9] described the design and implementation of a Network Virtualization Substrate (NVS) for effective virtualization of wireless resources in cellular networks. In their follow-up work, they considered a similar problem in [10] and presented CellSlice, which is a gateway-level solution that achieves slicing without modifying the BS's MAC scheduler. Furthermore, they extended their research to multiple BSs in a recent work [13]. Nakauchi *et al.* [14] proposed AMPHIBIA, which enables end-to-end slicing over wired and wireless networks and exploits the advantages of virtualization and cognitive radio technology. Zhu *et al.* [30] introduced the first TDD WiMAX-based SDR implementation on a commodity server, in conjunction with a novel design of a remote radio head. Li *et al.* [12] presented a software defined cellular network architecture that supports flexible slicing of network resource. Unlike the cloud-based RANs introduced in [3] and [18], SoftRAN [6] and the proposed CogCloud employs centralized control but still processes wireless signals at BSs (rather than in a data center) in a distributed manner. However, it does not support virtualization or multiple MVNOs, and moreover, the corresponding paper [6] did not present any resource allocation algorithms to enable the proposed architecture. More wireless virtualization works can be found in [2], [7], [12], [21], [24], [25] and [30]. All these related works studied how to enable virtualization in specific wireless networks. We, however, present a general auction-based model and mechanisms for resource sharing among MVNOs in a wireless network, assuming virtualization is enabled on BSs. Most related works (except [13], [17]) on virtualization were focused on a single BS. We, however, aim to support RaaS for MVNOs over a network with multiple BSs.

The auction theory has been studied for decades. Vickery [19] proposed the notion of truthful bidding in a sealed-bid auction, and introduced the second-price auctions. Clarke and Groves extended his work, yielding the famous Vickery-Clarke-Groves (VCG) mechanism [15]. It has been proved in [15] that every VCG mechanism is truthful (incentive compatible). In the meanwhile, to mitigate high time complexity of VCG, some works were focused on proposing fast greedy heuristic algorithms without sacrificing truthfulness [1], [23].

Recently, efforts have been made to apply the auction theory to support network virtualization. Gandhi *et al.* [5] proposed a real-time spectrum auction framework to distribute spectrum among a large number wireless users under interference constraints. Their approach achieves conflict-free spectrum allocations that maximize auction revenue and spectrum utilization. Sengupta *et al.* [16] presented a winner determining sealed-bid knapsack auction mechanism that dynamically allocates spectrum to the wireless service providers based on their bids. The proposed dynamic pricing strategy is based on game theory to capture the conflict of interest between wireless service providers and end users, both of whom try to maximize their respective net utilities. In [28], based on a non-cooperative game model, Zhou *et al.* presented a bandwidth allocation scheme with Nash Equilibrium for a virtualized network environment. However, these works have not considered truthfulness, which is one of the major design goals of our work.

Auction mechanisms have also been proposed for spectrum trading. Zhu *et al.* [33] proposed to design core selecting auctions, which resolve VCG's vulnerability to collusion and shill bidding and improve seller revenue. The core-selection auctions guarantee both efficiency and shill-proofness and outperform VCG auctions in terms of seller revenue. In [32], an efficient VCG mechanism was proposed for non-identical channel allocation among r-minded bidders in two different cases. In the first case, the bidders can submit bids only for single channels; in the second case, the bidders can submit bids for bundles of channels. Even though the payment rules of [33] tended to minimize the deviations from truthfulness, the absolute truthfulness was compromised. Tehrani and Uysal [32] focused on a single BS, and could not show truthfulness of the proposed methods either.

In addition, in [4], the interactions among Service Providers (SP) and Network Provider (NP) were modeled as a stochastic game; each stage of the game is played by SPs (on behalf of end users) and is regulated by the NP through a VCG mechanism. In [26], a truthful and computationally efficient spectrum auction named VERITAS was proposed to support eBay-like dynamic spectrum market with the objective of maximizing spectrum utilization. In [27], a general framework for truthful double spectrum auctions named TRUST is proposed. TRUST takes as input any reusability-driven spectrum allocation algorithm, and applies a winner determination and pricing mechanism to achieve truthfulness and other economic properties while improving spectrum utilization. Our work represents the first work to study the auction design for RaaS, which is mathematically different from the problems considered in these related works. We extend the early conference version [20] by introducing reserve prices, presenting action mechanism with reserve prices, and showing that they are truthful and individually rational in Section VI. We also justify their effectiveness via simulation results in Section VII-B.

TABLE I
NOTATIONS

Notation	Explanation
i, N and $\mathbf{I}$	The index of BSs, the total number of BSs and the set of BSs
j, M and $\mathbf{J}$	The index of MVNOs, the total number of MVNOs and the set of MVNOs
r_i and $\mathbf{R}$	Available dynamic resources of BS i and the corresponding vector
v_j and w_j	True valuation and declared valuation of MVNO j
$\mathbf{Y_j}$ and $\mathbf{Z_j}$	True demanded dynamic resource vector and declared dynamic resource vector of MVNO j
$\mathbf{b_j}$ and $\mathbf{B}$	Bid of MVNO j and the corresponding bid vector
x_j and $\mathbf{x}$	Winner selection variable and the corresponding vector
p_j and $\mathbf{p}$	Payment of MVNO j and the corresponding vector
u_i and $\mathbf{U}$	Price of BS i and the corresponding vector
f_j and $\mathbf{F}$	Reserve price of bid b_j and the corresponding vector

III. System Model and Auction Formulation

First of all, we summarize major notations in Table I

We consider an RaaS cloud with N BSs and M MVNOs. We adopt the resource-based provisioning model [9] for resource sharing among MVNOs: for a BS i, an MVNO j demands a slice (in terms of percentage) of its resources so that j can provide wireless service to its mobile users that are associated with BS i. In our model, resources of BSs are allocated to MVNOs in a hybrid way (both statically and dynamically). In a statical manner, an MVNO j reserves certain percent of the total resources at each BS i (denoted by $\overline{r_{ij}}$) for a long period of time (e.g., a month or a quarter) and makes the corresponding payment in advance according to a long-term forecasting for user traffic demands based on historical data. These resources are called static resources and are guaranteed to be available for MVNO j. An MVNO pays a certain amount of money to obtain such static resources (that are given as input to the auction mechanism). How to determine this kind of payment is out of scope of this paper.

However, since both user traffic demands and link data rates are time-varying, static resources may not be sufficient for an MVNO for a certain short period of time. So we need to provide a way for MVNOs to request more resources from BSs according to its real-time needs. The remaining resources of BS i can be given by $r_i = 1 - \sum_{j=1}^{M} \overline{r_{ij}}$, which are referred to as *available dynamic resources* of BS i. $\mathbf{R} = (r_1, \ldots, r_i, \ldots, r_N)$ is a vector for available dynamic resources at each BS. Dynamic resource allocation is conducted periodically (e.g., once every 30min). Then the real-time demand of MVNO j at BS i can be given by $y_{ij} = \max(d_{ij} - \overline{r_{ij}}, 0)$, where d_{ij} is the fraction of resources needed by MVNO j at BS i, which can be estimated according to current link data rates and user traffic demands. $\mathbf{Y_j} = (y_{1j}, \ldots, y_{ij}, \ldots y_{Nj})$ denotes the *demanded dynamic resource vector* of MVNO j.

RaaS can be formulated as an auction mechanism design problem. In the RaaS auction, the seller (i.e., the cloud service provider) sells available dynamic resources to bidders or buyers (i.e., MVNOs) who bid for them. Each MVNO j is asked to declare a bid $\mathbf{b_j} = (w_j, \mathbf{Z_j})$, where w_j is the valuation and $\mathbf{Z_j} = (z_{1j}, \dots, z_{ij}, \dots, z_{Nj})$ is the declared dynamic resource vector. Note that the true valuation v_j and the true demanded dynamic resource vector $\mathbf{Y_j}$ are private information only known to MVNO j. So w_j and $\mathbf{Z_j}$ could be different from v_j and $\mathbf{Y_j}$ respectively. However, in a truthful auction, a bidder does not want to declare a $\mathbf{Z}_j$ that is different from $\mathbf{Y}_j$ (which is explained later). The true valuation v_j may be determined based on many factors, such as static resources $\overline{r_{ij}}$, the demanded dynamic resource vector $\mathbf{Y}_j$, the number of its customers, the distribution of its customers, its revenue, its operating costs, etc. Note that this value is given as input to the auction mechanism. How to determine it is MVNO-dependent and is out of scope of this paper. Each MVNO j is a "single-minded bidder [1], [15], [31]" in the sense that valuation is v_j if it gets dynamic resource no less than $\mathbf{Y_j}$ and 0 otherwise. $\mathbf{B} = (\mathbf{b_1}, \dots, \mathbf{b_j}, \dots, \mathbf{b_M})$ is the bid vector. We use $\mathbf{B_{-j}}$ to denote the bids of all bidders except j, so $\mathbf{B} = (\mathbf{b_j}, \mathbf{B_{-j}})$.

RaaS auction takes $\mathbf{B}$ and $\mathbf{R}$ as input, and the output includes a winner vector $\mathbf{x}(\mathbf{B}, \mathbf{R}) = (x_1, \dots, x_j, \dots, x_M)$ and a payment vector $\mathbf{p}(\mathbf{B}, \mathbf{R}) = (p_1, \dots, p_j, \dots, p_M)$. $x_j = 1$ if bidder j wins and is allocated the declared dynamic resources $\mathbf{Z_j}$; $x_j = 0$, otherwise. p_j is the payment bidder j will make to the seller. The dynamic resource allocation must satisfy the following constraints: $\sum_{j=1}^{M} z_{ij} x_j \le r_i, \forall i \in \mathbf{I}$. Based on the output of the auction, the *payoff* [15] of bidder j is defined as

$$u_j = \begin{cases} v_j - p_j, & x_j = 1; \\ 0, & x_j = 0. \end{cases} \tag{1}$$

The *social welfare* [15] is defined as the total valuation of all winning bidders, i.e., $\sum_{j=1}^{M} v_j x_j$.

When designing an auction mechanism, it is desirable to have the following three properties [15]:

- **Individual Rationality**: an auction mechanism is *individually rational* if for any bidder j, the payoff is non-negative when bidder j bids its true value $(v_j, \mathbf{Y_j})$.
- **Truthfulness**: an auction mechanism is *truthful* if and only if for every bidder j and $\mathbf{B_{-j}}$, bidder j will not increase its payoff by making any other bid $(w_j, \mathbf{Z_j})$ instead of its true value $(v_j, \mathbf{Y_j})$; i.e., bidder j's payoff for bidding $(v_j, \mathbf{Y_j})$ is at least its payoff for bidding any other bid $(w_j, \mathbf{Z_j})$.
- **Computational Efficiency**: an auction mechanism is *computationally efficient* if the outcome can be computed in polynomial time.

Among these three properties, truthfulness is the most challenging one to achieve. In order to design a truthful auction mechanism, we introduce the following definitions.

Definition 1 (w-Monotonicity): if bidder j wins by bidding $(w_j^*, (z_{1j}^*, \dots, z_{ij}^*, \dots, z_{Nj}^*))$, then it also wins by bidding $(w_j', (z_{1j}^*, \dots, z_{ij}^*, \dots, z_{Nj}^*))$ with any $w_j' \ge w_j^*$.

Definition 2 (z-Monotonicity): if bidder j wins by bidding $(w_j^*, (z_{1j}^*, \dots, z_{ij}^*, \dots, z_{Nj}^*))$, then it also wins by bidding $(w_j^*, (z_{1j}', \dots, z_{ij}', \dots, z_{Nj}'))$ with all $z_{ij}' \le z_{ij}^*$.

Definition 3 (Critical Payment [15]): the payment p_j for winning bidder j is set to the critical value c_j such that bidder j wins if $w_j > c_j$, and loses if $w_j < c_j$.

Lemma 1: In an RaaS auction mechanism, if w-Monotonicity, z-Monotonicity and Critical Payment are satisfied, a bidder will not increase its payoff by bidding $(v_j, \mathbf{Z_j}) = (v_j, (z_{1j}, \dots, z_{ij}, \dots, z_{Nj}))$ instead of $(v_j, \mathbf{Y_j}) = (v_j, (y_{1j}, \dots, y_{ij}, \dots, y_{Nj}))$, where $\mathbf{Y_j} \ne \mathbf{Z_j}$.

Proof: We examine two possible cases:

1) $z_{ij} < y_{ij}$ for one or more i. In this case, by bidding $(v_j, \mathbf{Z_j})$, the payoff is non-positive since the valuation is 0 when single-minded bidder j's resource demand $\mathbf{Y_j}$ cannot be met. However, the payoff of bid $(v_j, \mathbf{Y_j})$ is non-negative because if $(v_j, \mathbf{Y_j})$ is a losing bid, the payoff is 0; if $(v_j, \mathbf{Y_j})$ is a winning bid, the payoff will be non-negative.

2) $z_{ij} \ge y_{ij}$ for every i. Denote the Critical Payment for bidding $(v_j, \mathbf{Y_j})$ by p, and denote the Critical Payment for bidding $(v_j, \mathbf{Z_j})$ by p^*. Based on z-Monotonicity, we know that if a bidder loses by bidding $(v_j, \mathbf{Y_j})$, it will also lose by bidding $(v_j, \mathbf{Z_j})$. Or equivalently, for any $v_j < p$, we have $v_j < p^*$. So $p^* \ge p$. We have two sub-cases: *a*) $(v_j, \mathbf{Z_j})$ is a losing bid. In this sub-case, the payoff of bid $(v_j, \mathbf{Y_j})$ is non-negative because if $(v_j, \mathbf{Y_j})$ is a losing bid, the payoff is 0; if $(v_j, \mathbf{Y_j})$ is a winning bid, the payoff will be non-negative. *b*) $(v_j, \mathbf{Z_j})$ is a winning bid. In this sub-case, a bidder with $(v_j, \mathbf{Y_j})$ will also win and the payment will not increase. ■

Theorem 1: An RaaS auction mechanism is truthful, if it satisfies w-Monotonicity, z-Monotonicity and Critical Payment.

Proof: According to the above definition of truthfulness, we will show that a bidder will not increase its payoff by bidding any other bid $(w_j, \mathbf{Z_j}) = (w_j, (z_{1j}, \dots, z_{ij}, \dots, z_{Nj}))$ instead of $(v_j, \mathbf{Y_j}) = (v_j, (y_{1j}, \dots, y_{ij}, \dots, y_{Nj}))$. We will first show that a bidder will not increase its payoff by bidding $(w_j, \mathbf{Z_j})$ instead of $(v_j, \mathbf{Z_j})$, where $v_j \ne w_j$. Denote the Critical Payment for bidding $(v_j, \mathbf{Z_j})$ by p. We have two cases:

1) $(v_j, \mathbf{Z_j})$ is a losing bid. In this case, $v_j < p$. If a bidder with $(w_j, \mathbf{Z_j})$ loses, it would not be more beneficial than bidding $(v_j, \mathbf{Z_j})$. If a bidder with $(w_j, \mathbf{Z_j})$ wins, it makes the same payment p because the Critical Payment is independent of w_j; since $p > v_j$, the payoff of bidding $(w_j, \mathbf{Z_j})$ is negative.

2) $(v_j, \mathbf{Z_j})$ is a winning bid. If $w_j > p$, a bidder with $(w_j, \mathbf{Z_j})$ wins with the same payment p. If $w_j < p$, a bidder with $(w_j, \mathbf{Z_j})$ loses with 0 payoff.

The above two cases show that a bidder will not increase its payoff by bidding $(w_j, \mathbf{Z_j})$ instead of $(v_j, \mathbf{Z_j})$. Furthermore, in Lemma 1, we have proved that a bidder will not increase its payoff by bidding $(v_j, \mathbf{Z_j})$ instead of $(v_j, \mathbf{Y_j})$. Therefore, a bidder will not increase its payoff by bidding any other $(w_j, \mathbf{Z_j})$ instead of $(v_j, \mathbf{Y_j})$. This completes the proof. ■

IV. Auction Mechanism With Optimal Social Welfare

In this section, we present a VCG-based (Vickery-Clarke-Groves [15]) auction mechanism that can achieve optimal social welfare.

A. Optimal RaaS Auction Design (Optimal-RaaS)

The RaaS auction design problem consists of two subproblems: Winner Selection and Price Determination. The Winner Selection problem can be formulated as the following Integer Linear Programming (ILP) problem:
ILP-Winner

$$\max \sum_{j \in \mathbf{J}} w_j x_j \tag{2}$$

Subject to:

$$\sum_{j \in \mathbf{J}} z_{ij} x_j \le r_i, \quad \forall i \in \mathbf{I}; \tag{3}$$

$$x_j \in \{0, 1\}, \quad \forall j \in \mathbf{J}; \tag{4}$$

The objective is to maximize the social welfare. Constraints (3) ensure that for each BS, the sum of demanded dynamic resources does not exceed its available dynamic resources. Denote the optimal value of the ILP by $\Psi(\mathbf{B})$. Next, we present an auction mechanism that can achieve optimal social welfare, which is referred to as *Optimal-RaaS*.

(1) Winner Selection: select winners $\mathbf{x}^*$ by solving ILP-Winner;
(2) Price Determination: $p_j := \Psi(\mathbf{B_{-j}}) - (\Psi(\mathbf{B}) - w_j)$ if $x_j^* = 1$ and $p_j := 0$ otherwise. $\Psi(\mathbf{B_{-j}})$ is the optimal value of ILP-Winner with bid $\mathbf{b_j}$ removed.

B. Proof of Properties

Although Optimal-RaaS is VCG-based, the proofs of properties are non-trivial because the bids in RaaS model are multidimensional [11]. In order to prove the truthfulness of Optimal-RaaS, we show that the Winner Selection satisfies w-Monotonicity and z-Monotonicity. Furthermore, the Critical Payment condition is satisfied by the Price Determination.

Lemma 2: w-Monotonicity is satisfied in the Winner Selection of Optimal-RaaS.

Proof: Suppose that bidder j wins by bidding $\mathbf{b_j^*} = (w_j^*, (z_{1j}^*, \ldots, z_{ij}^*, \ldots, z_{Nj}^*))$. Let $\mathbf{x}$ be the winner vector. We will prove that it also wins by bidding $\mathbf{b_j'} = (w_j', (z_{1j}^*, \ldots, z_{ij}^*, \ldots, z_{Nj}^*))$ with any $w_j' > w_j^*$ by contradiction. Suppose it will lose by bidding $\mathbf{b_j'}$. Then $\Psi((\mathbf{b_j'}, \mathbf{B_{-j}})) = \Psi(\mathbf{B_{-j}})$. Since bidder j wins by bidding $\mathbf{b_j^*}$, $\Psi(\mathbf{B_{-j}}) < \Psi((\mathbf{b_j^*}, \mathbf{B_{-j}}))$. Therefore $\Psi((\mathbf{b_j'}, \mathbf{B_{-j}})) < \Psi((\mathbf{b_j^*}, \mathbf{B_{-j}}))$. Having the same winner vector $\mathbf{x}$, the social welfare with $(\mathbf{b_j'}, \mathbf{B_{-j}})$ would be greater than the social welfare with $(\mathbf{b_j^*}, \mathbf{B_{-j}})$, because $w_j' > w_j^*$; this contradicts the statement that $\Psi((\mathbf{b_j'}, \mathbf{B_{-j}})) < \Psi((\mathbf{b_j^*}, \mathbf{B_{-j}}))$. Hence the supposition is false, and bidder j will also win by bidding $\mathbf{b_j'}$. This completes the proof. ■

Lemma 3: z-Monotonicity is satisfied in the Winner Selection of Optimal-RaaS.

Proof: Suppose that bidder j wins by bidding $\mathbf{b_j^*} = (w_j^*, (z_{1j}^*, \ldots, z_{ij}^*, \ldots, z_{Nj}^*))$. Let $\mathbf{x}$ be the winner vector. We will prove that it also wins by bidding $\mathbf{b_j'} = (w_j^*, (z_{1j}^*, \ldots, z_{ij}', \ldots, z_{Nj}^*))$ with any $z_{ij}' < z_j^*$ by contradiction. Suppose it will lose by bidding $\mathbf{b_j'}$. Then $\Psi((\mathbf{b_j'}, \mathbf{B_{-j}})) = \Psi(\mathbf{B_{-j}})$. Since bidder j wins by bidding $\mathbf{b_j^*}$, $\Psi(\mathbf{B_{-j}}) < \Psi((\mathbf{b_j^*}, \mathbf{B_{-j}}))$. Therefore $\Psi((\mathbf{b_j'}, \mathbf{B_{-j}})) < \Psi((\mathbf{b_j^*}, \mathbf{B_{-j}}))$. Having the same winner vector $\mathbf{x}$, the social welfare with $(\mathbf{b_j'}, \mathbf{B_{-j}})$ is equal to $(b_j^*, \mathbf{B_{-j}})$; this contradicts the statement that $\Psi((\mathbf{b_j'}, \mathbf{B_{-j}})) < \Psi((\mathbf{b_j^*}, \mathbf{B_{-j}}))$. Hence the supposition is false, and bidder j will also win by bidding $\mathbf{b_j'}$. This completes the proof. ■

Lemma 4: $p_j = \Psi(\mathbf{B_{-j}}) - (\Psi(\mathbf{B}) - w_j)$ is a critical value for each winning bidder j in Optimal-RaaS.

Proof: In Optimal-RaaS, the payment of each winning bidder is calculated based on the opportunity cost [15], which is introduced to all the other bidders by the presence of the winning bidder. Therefore, if the bidder bids less than this price, it will not be selected as a winner, which leads to higher social welfare [23]. ■

Theorem 2: Optimal-RaaS is truthful.

Proof: According to Lemmas 2, 3 and 4 along with Theorem 1, Optimal-RaaS is truthful. ■

We then prove that Optimal-RaaS satisfies individual rationality.

Theorem 3: Optimal-RaaS is individually rational.

Proof: For any bidder j bidding its true value $(v_j, \mathbf{Y_j})$, we consider two possible cases: 1) Bidder j is a winner. Its payoff is $u_j = v_j - p_j = v_j - (\Psi(\mathbf{B_{-j}}) - (\Psi(\mathbf{B}) - v_j)) = \Psi(\mathbf{B}) - \Psi(\mathbf{B_{-j}}) \ge 0$, where the last inequality follows from the optimality of $\Psi(\mathbf{B})$. 2) Bidder j is not a winner. Its payoff is 0. This completes the proof. ■

V. Greedy Auction Mechanism

Although Optimal-RaaS is both individually rational and truthful, it is not computationally efficient since solving ILP-Winner may take exponential time. In this section, we present an auction mechanism, called Greedy RaaS Auction Design (GRAD), which has all the three desirable properties.

A. Greedy RaaS Auction Design (GRAD)

GRAD consists of two phases too: *Winner Selection* and *Price Determination*. In the *Winner Selection* (Algorithm 1), the basic idea is to keep adding the bidder with the largest weight to the solution. We adopt the following weight α_j as the metric for sorting bidders and selecting winners:

$$\alpha_j = \frac{w_j}{\sum_{i \in \mathbf{I}} \frac{z_{ij}}{r_i}}. \tag{5}$$

In each iteration, the bidder with the maximum weight α_j is selected as the winner. Then we update $\mathbf{R}$ by subtracting the corresponding demanded dynamic resource vector $\mathbf{Z_j}$ of the selected winner from it. All the bidders who demand more dynamic resources than the available resources in the updated $\mathbf{R}$ will be eliminated from the auction. This process iterates until the bidder list is empty.

In the *Price Determination* (Algorithm 2), to find the payment for a winning bidder j, we remove j from the bidder list, do the Winner Selection as above with the rest bidders until a winning bidder k is found such that its selection can disqualify j from winning the auction and determine the price accordingly (lines 9–10 in Algorithm 2).

Algorithm 1 Winner Selection of GRAD

Input : Bid vector $\mathbf{B}$ and Available dynamic resource vector $\mathbf{R}$
Output: Winner vector $\mathbf{x}$

1 $x_j := 0, \forall j \in \mathbf{J}$;
2 $\alpha_j := \frac{w_j}{\sum_{i \in \mathbf{I}} \frac{z_{ij}}{r_i}}, \forall j \in \mathbf{J}$;
3 Sort the bidders in the non-increasing order of α_j and store the sorted list of their indices into $\mathbf{L}$;
4 **while** $\mathbf{L} \neq \emptyset$ **do**
5   Let j be the next bidder in $\mathbf{L}$;
6     $x_j := 1$;
7     $\mathbf{L} := \mathbf{L} \setminus \{j\}$;
8     $\mathbf{R} := \mathbf{R} - \mathbf{Z_j}$;
9   **forall the** $m \in \mathbf{L}$ **do**
10   **if** $\exists i \in \mathbf{I}$ *s.t.* $z_{im} > r_i$ **then**
11             $\mathbf{L} := \mathbf{L} \setminus \{m\}$;
12
13 **return** $\mathbf{x}$;

Algorithm 2 Price Determination of GRAD

Input : Bid vector $\mathbf{B}$, Available dynamic resource vector $\mathbf{R}$, Winner vector $\mathbf{x}$, Sorted bidder list $\mathbf{L}$ and weight $\alpha_j, \forall j \in \mathbf{J}$
Output: Payment vector $\mathbf{p}$

1 **forall the** $j \in \mathbf{L}$ **do**
2     $p_j := 0$;
3   **if** $x_j = 1$ **then**
4         $\mathbf{L}' := \mathbf{L} \setminus \{j\}$; $\mathbf{R}' := \mathbf{R}$;
5   **while** $\mathbf{L}' \neq \emptyset$ **do**
6   Let k be the next bidder in $\mathbf{L}'$;
7             $\mathbf{L}' := \mathbf{L}' \setminus \{k\}$;
8             $\mathbf{R}' := \mathbf{R}' - \mathbf{Z_k}$;
9   **if** $\exists i \in \mathbf{I}$ *s.t.* $z_{ij} > r'_i$ **then**
10                 $p_j := (\alpha_k \sum_i \frac{z_{ij}}{r_i})$; break;
11   **forall the** $m \in \mathbf{L}'$ **do**
12   **if** $\exists i \in \mathbf{I}$ *s.t.* $z_{im} > r'_i$ **then**
13                     $\mathbf{L}' := \mathbf{L}' \setminus \{m\}$;
14
15
16 **return** $\mathbf{p}$;

B. Proof of Properties

Lemma 5: w-Monotonicity is satisfied in the Winner Selection of GRAD.

Proof: Suppose that bidder j wins by bidding $(w_j^*, \mathbf{Z_j^*}) = (w_j^*, (z_{1j}^*, \ldots, z_{ij}^*, \ldots, z_{Nj}^*))$. We prove that it will also win by bidding $(w'_j, \mathbf{Z_j^*}) = (w'_j, (z_{1j}^*, \ldots, z_{ij}^*, \ldots, z_{Nj}^*))$ with any $w'_j > w_j^*$. Let $\mathbf{L}^*$ and $\mathbf{L}'$ denote the sorted lists when j bids $(w_j^*, \mathbf{Z_j^*})$ and $(w'_j, \mathbf{Z_j^*})$ respectively. The positions of j in $\mathbf{L}^*$ and $\mathbf{L}'$ are denoted by q^* and q' respectively. Since $\alpha'_j = \frac{w'_j}{\sum_{i=1}^N \frac{z_{ij}}{r_i}} > \alpha_j^* = \frac{w_j^*}{\sum_{i=1}^N \frac{z_{ij}}{r_i}}$, it is clear that $q' \le q^*$. Furthermore, at lines 9–11 in Algorithm 1, since j has not been eliminated at q^*, it will not be eliminated at q' neither. Therefore, j will still win with bid $(w'_j, \mathbf{Z_j^*})$. ■

Lemma 6: z-Monotonicity is satisfied in the Winner Selection of GRAD.

Proof: Suppose that bidder j wins by bidding $(w_j^*, \mathbf{Z_j^*}) = (w_j^*, (z_{1j}^*, \ldots, z_{ij}^*, \ldots, z_{Nj}^*))$. We prove that it will also win by bidding $(w_j^*, \mathbf{Z'_j}) = (w_j^*, (z_{1j}^*, \ldots, z'_{ij}, \ldots, z_{Nj}^*))$ with any $z'_{ij} < z_{ij}^*$. Let $\mathbf{L}^*$ and $\mathbf{L}'$ denote the sorted lists when j bids $(w_j^*, \mathbf{Z_j^*})$ and $(w_j^*, \mathbf{Z'_j})$ respectively; the positions of j in $\mathbf{L}^*$ and $\mathbf{L}'$ are denoted by q^* and q' respectively. For the sake of presentation, denote $\sum_{i=1}^N \frac{z_{ij}}{r_i}$ by $s(\mathbf{Z_j})$. With $z'_{ij} < z_{ij}^*$, we have $s(\mathbf{Z'_j}) < s(\mathbf{Z_j^*})$. So $\alpha'_j = \frac{w_j^*}{s(\mathbf{Z'_j})} > \alpha_j^* = \frac{w_j^*}{s(\mathbf{Z_j^*})}$; thus $q' \le q^*$. Furthermore, at lines 9–11 in Algorithm 1, since j has not been eliminated at q^*, it will not be eliminated at q' neither. Therefore, j will still win with bid $(w_j^*, \mathbf{Z'_j})$. ■

Lemma 7: The payment p_j is set to a critical value for each winning bidder j in GRAD.

Proof: Let k be the first bidder in the list, whose selection can disqualify j. Let $c_j = \alpha_k \sum_{i=1}^N \frac{z_{ij}}{r_i}$. If bidder j bids $w_j < c_j$, then $\alpha_j < \alpha_k$, meaning j will be placed behind k in the sorted list and thus will be eliminated from the auction. If bidder j bids $w_j > c_j$, then $\alpha_j > \alpha_k$, meaning j will be placed ahead of k. j is ahead of any bidder that can disqualify j, because k is the first of such bidders. Therefore j will be selected as a winner and c_j is the critical value for winning bidder j. Since the payment p_j is set to c_j in the algorithm, we prove the lemma. ■

Theorem 4: GRAD is truthful.

Proof: According to Lemmas 5, 6 and 7 along with Theorem 1, GRAD is truthful. ■

Theorem 5: GRAD is individually rational.

Proof: We consider two possible cases: 1) Bidder j is not a winner. From Algorithm 2, j pays 0. Therefore its payoff is 0. 2) Bidder j is a winner. Since GRAD satisfies the Critical Payment property as shown in Lemma 7, we have $w_j > c_j = p_j$. In a truthful mechanism, $w_j = v_j$. Hence we have $v_j - p_j > 0$. Therefore the payoff is always non-negative. This completes the proof. ■

Next, we show that *GRAD is computationally efficient.* We can see that in Algorithm 1, calculating α (line 2) takes $O(MN)$ time. Furthermore, the while-loop (lines 4–11) takes $O(M^2N)$ time. Hence time complexity of Algorithm 1 is $O(M^2N)$. In Algorithm 2, the for-loop takes $O(M^3N)$ time, since the for-loop (lines 1–13) runs M iterations, and in each iteration, while-loop (lines 5–13) takes $O(M^2N)$ time. So the time complexity of Algorithm 2 is $O(M^3N)$. Therefore, the overall time complexity of GRAD is $O(M^3N)$.

VI. Auction Mechanisms With Reserve Prices

Optimal-RaaS and GRAD are both individually rational and truthful. Moreover, Optimal-RaaS can achieve optimal social welfare and GRAD is computationally efficient with sub-optimal social welfare. However, there is an issue that the Price Determination of Optimal-RaaS and GRAD might end up with 0 payment for some winners. To be more specific, in Optimal-RaaS with more available dynamic resources, for some win-

Algorithm 3 Bidder Screening of RaaS-RP

```
Input  : Bid vector B, Bidder set J and BS price vector U
Output : Remaining bidder set J' and Reserve price vector F
f_j := Σ_{i∈I} u_i z_ij, ∀j ∈ J;
forall the j ∈ J do
    if f_j > w_j then
        x_j := 0;
        J := J \ j;
J' := J;
return J', F;
```

ning bidders, it turns out that $\Psi(\mathbf{B_{-j}}) = (\Psi(\mathbf{B}) - w_j)$, yielding 0 payment. In GRAD, with more available dynamic resources, there is a higher chance that for some winning bidders, the *if* condition of line 9 will not be satisfied; therefore line 10 will not be executed, resulting in 0 payments.

In order to mitigate this problem and grant more right to the seller to determine the payment, we introduce the following definition [11]:

Definition 4 (Reserve Price): The seller reserves the right not to sell the declared dynamic resource of $\mathbf{Z_j}$ if the payment determined is lower than some threshold price. Such a threshold price is called a *reserve price*, denoted by f_j.

It is desirable to have reserve prices, whose values are closely related to declared dynamic resources of each BS. There may be multiple options to calculate such reserve prices. We choose to use the following formulation:

$$f_j = \sum_{i \in \mathbf{I}} u_i z_{ij}, \quad \forall j \in \mathbf{J}; \tag{6}$$

where u_i is the price of BS i, i.e., the price of allocating 100% of the resources of BS i. Next, we present the auction mechanism with reserve prices.

A. RaaS Auction With Reserve Prices (RaaS-RP)

The RaaS auction mechanism design problem with Reserve Prices (RaaS-RP) consists of three subproblems: Bidder Screening, Winner Selection and Price Determination.

(1) Bidder Screening: use Algorithm 3;
(2) Winner Selection: solve the Winner Selection problem of Optimal-RaaS or GRAD with $\mathbf{J}'$ (instead of $\mathbf{J}$);
(3) Price Determination: $p_j := \max\{f_j, p_j^*\}$, if $x_j^* = 1$ and $p_j := 0$ otherwise. p_j^* is the payment determined by Optimal-RaaS or GRAD.

Note that we have integrated the reserve prices f_j in the Bidder Screening and Price Determination. In the Bidder Screening, those bidders with declared valuation $w_j < f_j$, will be screened out of the auction. In the Price Determination, $p_j = \max\{f_j, p_j^*\}$, ensuring the payment p_j is no less than the reserve price f_j. Note that RaaS-RP is designed on the basis of Optimal-RaaS or GRAD, so RaaS-RP could be either Optimal-RaaS with reserve prices (Optimal-RaaS-RP) or GRAD with reserve prices (GRAD-RP).

B. Proof of Properties

In order to prove the truthfulness of RaaS-RP, we will prove that w-Monotonicity, z-Monotonicity and Critical Payment condition will all be satisfied.

Lemma 8: w-Monotonicity is satisfied in RaaS-RP.

Proof: Suppose that bidder j wins by bidding $\mathbf{b_j^*} = (w_j^*, (z_{1j}^*, \dots, z_{ij}^*, \dots, z_{Nj}^*))$. We will prove that it also wins by bidding $\mathbf{b_j'} = (w_j', (z_{1j}^*, \dots, z_{ij}^*, \dots, z_{Nj}^*))$ with any $w_j' > w_j^*$. Let f_j^* be the reserve price of $\mathbf{b_j^*}$ and f_j' be the reserve price of $\mathbf{b_j'}$. In the Bidder Screening, since j wins by bidding $\mathbf{b_j^*}$, it is clear that $f_j^* \le w_j^*$. By bidding $\mathbf{b_j'}$, the reserve price $f_j' = f_j^*$; therefore $w_j' > f_j'$. Bidder j will not be screened out by bidding $\mathbf{b_j'}$. In the Winner Selection, from Lemma 2 and Lemma 5, if bidder j wins by bidding $\mathbf{b_j^*}$, it also wins by bidding $\mathbf{b_j'}$ in Optimal-RaaS or GRAD. This completes the proof. ■

Lemma 9: z-Monotonicity is satisfied in RaaS-RP.

Proof: Suppose that bidder j wins by bidding $(w_j^*, \mathbf{Z_j^*}) = (w_j^*, (z_{1j}^*, \dots, z_{ij}^*, \dots, z_{Nj}^*))$. We prove that it will also win by bidding $(w_j^*, \mathbf{Z_j'}) = (w_j^*, (z_{1j}^*, \dots, z_{ij}', \dots, z_{Nj}^*))$ with any $z_{ij}' < z_{ij}^*$. Let f_j^* be the reserve price of $(w_j^*, \mathbf{Z_j^*})$ and f_j' be the reserve price of $(w_j^*, \mathbf{Z_j'})$. In the Bidder Screening, since j wins by bidding $(w_j^*, \mathbf{Z_j^*})$, it is clear that $f_j^* \le w_j^*$. By bidding $\mathbf{b_j'}$, the reserve price $f_j' < f_j^*$; therefore $w_j^* > f_j'$. Bidder j will not be screened out by bidding $\mathbf{b_j'}$. In the Winner Selection, from Lemma 3 and Lemma 6, if bidder j wins by bidding $(w_j^*, \mathbf{Z_j^*})$, it also wins by bidding $(w_j^*, \mathbf{Z_j'})$ in Optimal-RaaS or GRAD. This completes the proof. ■

Lemma 10: $p_j = \max\{f_j, p_j^*\}$ is a critical value for each winning bidder j in RaaS-RP.

Proof: Let $c_j = \max\{f_j, p_j^*\}$. We now examine the following two cases:

1) If bidder j bids $w_j < c_j$, then we have either $w_j < f_j$ or $w_j < p_j^*$. We now discuss these two cases: 1) $w_j < f_j$. In this case, bidder j will be screened out in the Bidder Selection of RaaS-RP. 2) $w_j < p_j^*$. In this case, since p_j^* is the critical value for winning bidder j in Optimal-RaaS or GRAD, j will not be selected as a winner according to Lemma 4 and Lemma 7. Therefore in either of the cases, bidder j will not win if $w_j < c_j$.

2) If bidder j bids $w_j > c_j$, it is clear that $w_j > f_j$ and $w_j > p_j^*$. Hence j will not be screened out of the auction in the Bidder Screening, and furthermore, it will be selected as a winner according to Lemma 4 and Lemma 7.

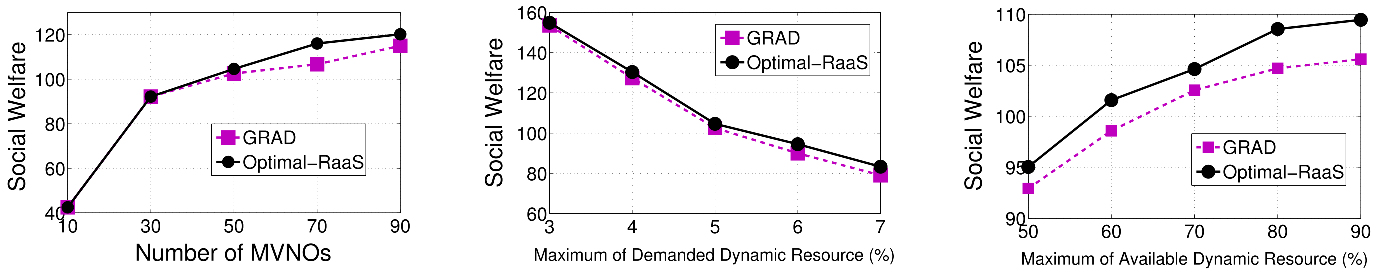
Therefore, c_j is the critical value for winning bidder j. Since the payment p_j of RaaS is set to c_j, we prove the lemma. ■

Theorem 6: RaaS-RP is truthful.

Proof: According to Lemmas 8, 9 and 10 along with Theorem 1, RaaS-RP is truthful. ■

Theorem 7: RaaS-RP is individually rational.

Proof: For any bidder j bidding its true value $(v_j, \mathbf{Y_j})$, we consider two possible cases: 1) Bidder j is a winner. Its payoff is $u_j = v_j - p_j = v_j - \max\{f_j, p_j^*\}$. For a winning bidder, $w_j > f_j$; in a truthful mechanism, $w_j = v_j$. Hence we have $v_j > f_j$. Meanwhile, in Theorem 3 and Theorem 5, we have proved $v_j > p_j$ for a win-



(a) Scenario 1 (b) Scenario 2 (c) Scenario 3

Fig. 3. Social welfare. (a) Scenario 1. (b) Scenario 2. (c) Scenario 3.

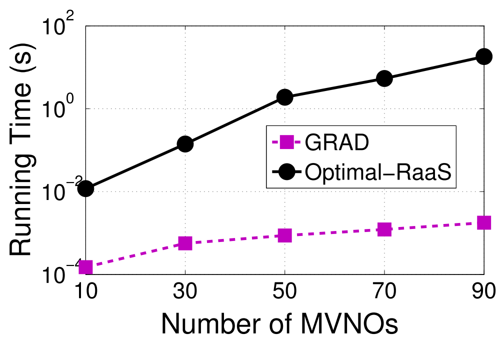


Fig. 2. Running time.

ning bidder. Therefore $u_j = v_j - \max\{f_j, p_j^*\} > 0$. 2) Bidder j is not a winner. Its payoff is 0. This completes the proof. ■

VII. Performance Evaluation

In this section, we present simulation settings and discuss simulation results to justify the effectiveness of the proposed auction design.

The simulation runs were conducted on a computer with a 2.5GHz Intel i5 CPU and 4GB memory. The social welfare is given in terms of credits, whose monetary worth can be determined by the cloud service provider (seller). In the simulation, there were 40 BSs in total.

A. Performance Evaluation of Optimal-RaaS and GRAD

We evaluated the performance of Optimal-RaaS and GRAD in terms of running time and social welfare by varying the number of MVNOs (bidders), the demanded dynamic resources and the available dynamic resources. Specifically, we came up with the following 3 scenarios for our simulation. All the numbers presented in the figures are averages over 20 runs.

1) In Scenario 1, the demanded dynamic resources were uniformly distributed in $[0\%, 5\%]$; the available dynamic resources followed a uniform distribution in $[50\%, 70\%]$. The number of MVNOs was increased from 10 to 90 with a step size of 20. The corresponding results are presented in Figs. 2 (running time) and 3(a) (social welfare).

2) In Scenario 2, the number of MVNOs was fixed to 50; the available dynamic resources and demanded dynamic resources were uniformly distributed in $[50\%, 70\%]$ and $[0\%, u_1]$ respectively, where u_1 was increased from 3% to 7% with a step size of 1%. The corresponding results are presented in Fig. 3(b).

3) In Scenario 3, the number of MVNOs was fixed to 50; the demanded dynamic resources and available dynamic resources were uniformly distributed in $[0\%, 5\%]$ and $[50\%, u_2]$ respectively, where u_2 was increased from 50% to 90% with a step size of 10%. The corresponding results are presented in Fig. 3(c).

We can make the following observations from these results:

1) Fig. 2 shows the running times of the proposed mechanisms with various numbers of MVNOs. The running time of GRAD is $\frac{1}{78}$ of that of Optimal-RaaS on small cases with only 10 MVNOs. Running time savings become more and more significant when the number of MVNOs becomes larger and larger. Specifically, when it turns to 90, the running time of GRAD is about $\frac{1}{10{,}000}$ of that of Optimal-RaaS. This leads us to believe that substantial running time savings can be achieved by using GRAD.

2) Fig. 3 shows the performance of the the proposed methods with regard to social welfare. Social welfare values given by GRAD are always lower than (as expected), but close to the optimal ones. On average, by varying the number of MVNOs, the maximum demanded dynamic resource and maximum available dynamic resource, GRAD achieves 97.1%, 97.0% and 97.2% of optimal social welfare, respectively.

3) Monotonicity can be observed in Figure 3. Specifically, in Scenario 1, with more MVNOs to choose from, both methods lead to higher social welfare. In Scenario 2, more demanded dynamic resources result in fewer winning bidders (MVNOs), yielding lower social welfare. In Scenario 3, with larger available dynamic resource, more bidders are selected as winners, resulting in higher social welfare.

B. Performance Evaluation of RaaS-RP

With respect to RaaS-RP, we came up with 2 scenarios for our simulation. Scenario 4 is to reveal the fact that there may exist some winners with 0 payment in Optimal-RaaS and GRAD. Scenario 5 was developed to evaluate the performance of RaaS-RP in terms of running time and social welfare by varying BS prices. All the numbers presented in the figures are averages over 20 runs.

1) In Scenario 4, the number of MVNOs was fixed to 30; the demanded dynamic resources were uniformly distributed in

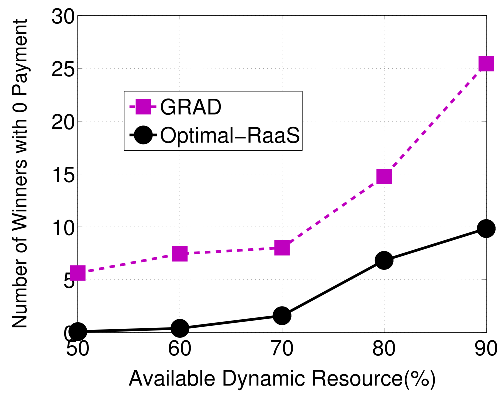


Fig. 4. Number of Winners with 0 Payment.

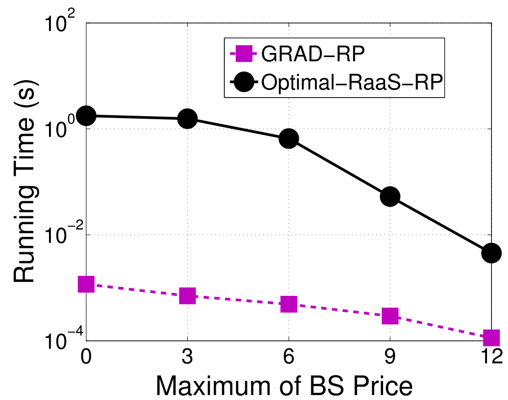


Fig. 5. Running Time of RaaS-RP.

[0%, 5%]; and the available dynamic resources were increased from 50% to 90% with a step size of 10%. The corresponding results are presented in Fig. 4.

2) In Scenario 5, the number of MVNOs was fixed to 50; the demanded dynamic resources and available dynamic resources were uniformly distributed in [0%, 5%] and [50%, 90%] respectively; the prices of BSs were uniformly distributed in $[0, u_3]$, where u_3 was increased from 0 to 12 with a step size of 3. The corresponding results are presented in Figs. 5 and 6.

We can make the following observations from these results:

1) Fig. 4 shows that for Optimal-RaaS and GRAD, in which there are no reserve prices, monotonicity can be observed between the number of winners with 0 payment and available dynamic resources. Specifically, with more available dynamic resources, both methods lead to more winners with 0 payment.

2) Fig. 5 shows that the running times of Optimal-RaaS-RP and GRAD-RP decrease with the increment of BS prices. The reason is, with higher BS prices, more bidders will be screened out of the auction in Bidder Screening of RaaS-RP because their declared valuation w_j is lower than the reserve price f_j. Moreover, the comparison of Optimal-RaaS-RP and GRAD-RP shows that running time savings are more significant when the BS price becomes lower. Specifically the running time of GRAD-RP is $\frac{1}{1123}$ of that of Optimal-RaaS-RP in the case of 0 price and $\frac{1}{76}$ with the maximum BS price of 12.

3) Fig. 6 shows the performance of Optimal-RaaS-RP and GRAD-RP with regards to social welfare. With the increment of BS prices, more bidders will be screened out of the auction, yielding lower social welfare. Furthermore, as expected, social

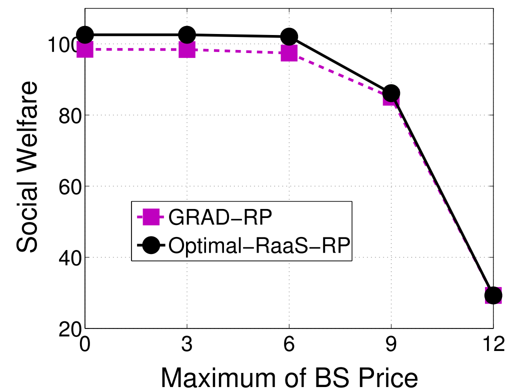


Fig. 6. Social Welfare of RaaS-RP.

welfare values given by GRAD-RP are always lower than but close to the Optimal-RaaS-RP; on average, GRAD-RP achieves 98.6% of optimal social welfare.

VIII. Conclusion

In this paper, we proposed a novel auction-based model for RaaS. Based on the proposed model, we studied the auction mechanism design with the objective of maximizing social welfare. First, we proposed Optimal-RaaS, which is an ILP and VCG based auction mechanism that can achieve optimal social welfare. To reduce time complexity, we proposed GRAD, which is a polynomial-time greedy mechanism for the RaaS auction. Both methods have been formally shown to be truthful and individually rational. Extensive simulation results show that GRAD can quickly produce close-to-optimal solutions. Furthermore, to prevent winning bidders from making 0 payment, we introduced reserve prices and presented Optimal-RaaS-RP and GRAD-RP, which were designed based on Optimal-RaaS and GRAD respectively. We have showed that both mechanisms are truthful and individually rational too.

References

[1] A. Archer, C. Papadimitriou, K. Talwar, and É. Tardos, "An approximate truthful mechanism for combinatorial auctions with single parameter agents," *Int. Math.*, vol. 1, no. 2, pp. 129–150, 2004.

[2] G. Bhanage, I. Seskar, R. Mahindra, and D. Raychaudhuri, "Virtual basestation: Architecture for an open shared WiMAX framework," in *Proc. ACM VISA*, 2010, pp. 1–8.

[3] S. Bhaumik *et al.*, "CloudIQ: A framework for processing base stations in a data center," in *Proc. ACM MobiCom*, 2012, pp. 125–136.

[4] F. Fu and U. C. Kozat, "Wireless network virtualization as a sequential auction game," in *Proc. IEEE INFOCOM*, Mar. 2010, pp. 1–9.

[5] S. Gandhi, C. Buragohain, L. Cao, H. Zheng, and S. Suri, "A general framework for wireless spectrum auctions," in *Proc. New Frontiers Dyn. Spectr. Access Netw.*, 2007, pp. 22–33.

[6] A. Gudipati, D. Perry, L. E. Li, and S. Katti, "SoftRAN: Software defined radio access network," in *Proc. ACM HotSDN*, 2013, pp. 25–30.

[7] M. M. Islam, M. M. Hassan, G.-W. Lee, and E.-N. Huh, "A survey on virtualization of wireless sensor networks," *IEEE Sensors J.*, vol. 12, no. 2, pp. 2175–2207, Dec. 2012.

[8] P. Klemperer, "What really matters in auction design," *J. Econ. Perspectives*, vol. 16, no. 1, pp. 169–189, 2002.

[9] R. Kokku, R. Mahindra, H. Zhang, and S. Rangarajan, "NVS: A substrate for virtualizing wireless resources in cellular networks," *IEEE/ACM Trans. Netw.*, vol. 20, no. 5, pp. 1333–1346, Jan. 2012.

[10] R. Kokku, R. Mahindra, H. Zhang, and S. Rangarajan, "CellSlice: Cellular wireless resource slicing for active RAN sharing," in *Proc. 5th Int. Conf. COMSNETS*, Jan. 2013, pp. 1–10.

[11] V. Krishan, *Auction Theory*. New York, NY, USA: Academic, 2009.

[12] L. Li, Z. M. Mao, and J. Rexford, "Cellsdn: Software-defined cellular networks," Princeton Univ. Press, Princeton, NJ, USA, Tech. Rep. TR-922-12, 2012.

[13] R. Mahindra, M. A. Khojastepour, H. Zhang, and S. Rangarajan, "Radio access network sharing in cellular networks," in *Proc. IEEE ICNP*, Oct. 2013, pp. 1–10.

[14] K. Nakauchi, K. Ishizu, H. Murakami, A. Nakao, and H. Harada, "AMPHIBIA: A cognitive virtualization platform for end-to-end slicing," in *Proc. IEEE ICC*, Jun. 2011, pp. 1–5.

[15] N. Nisan, T. Roughgarden, É. Tardos, and V. V. Vazirani, *Algorithmic Game Theory*. Cambridge, U.K.: Cambridge Univ. Press, 2007.

[16] S. Sengupta, M. Chatterjee, and S. Ganguly, "An economic framework for spectrum allocation and service pricing with competitive wireless service providers," in *Proc. New Frontiers Dyn. Spectr. Access Netw.*, Apr. 2007, pp. 89–98.

[17] X. Sheng, J. Tang, C. Gao, W. Zhang, and C. Wang, "Leveraging load migration and basestaion consolidation for green communications in virtualized cognitive radio networks," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 1267–1275.

[18] K. Sundaresan, M. Y. Arslan, S. Singh, S. Rangarajan, and S. V. Krishnamurth, "FluidNet: A flexible cloud-based radio access network for small cells," in *Proc. ACM MobiCom*, 2013, pp. 99–110.

[19] W. Vickrey, "Counterspeculation, auctions, and competitive sealed tenders," *J. Finance*, vol. 16, no. 1, pp. 8–37, 1961.

[20] J. Wang, D. Yang, J. Tang, and M. C. Gursoy, "Radio-as-a-service: Auction-based model and mechanisms," in *Proc. IEEE ICC*, Jun. 2015, pp. 3567–3572.

[21] L. Xia *et al.*, "Virtual WiFi: Bring virtualization from wired to wireless," in *Proc. ACM VEE*, 2011, pp. 181–192.

[22] D. Yang, X. Fang, and G. Xue, "Truthful auction for cooperative communications," in *Proc. ACM MobiHoc*, 2011, Art. no. 9.

[23] D. Yang, X. Fang, and G. Xue, "Truthful auction for cooperative communications with revenue maximization," in *Proc. IEEE ICC*, Jun. 2012, pp. 4888–4892.

[24] D. Yun and Y. Yi, "Virtual network embedding in wireless multihop networks," in *Proc. CFI*, 2011, pp. 30–33.

[25] Y. Zaki, L. Zhao, C. Goerg, and A. Timm-Giel, "LTE mobile network virtualization: Exploiting multiplexing and multi-user diversity gain," *Mobile Netw. Appl.*, vol. 16, no. 4, pp. 424–432, 2011.

[26] X. Zhou, S. Gandhi, S. Suri, and H. Zheng, "eBay in the sky: Strategy-proof wireless spectrum auctions," in *Proc. ACM MobiCom*, 2008, pp. 2–13.

[27] X. Zhou and H. Zheng, "TRUST: A general framework for truthful double spectrum auctions," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 999–1007.

[28] Y. Zhou, Y. Li, G. Sun, D. Jin, L. Su, and L. Zeng, "Game theory based bandwidth allocation scheme for network virtualization," in *Proc. IEEE Globecom*, Dec. 2010, pp. 1–5.

[29] H. Zhu and K. Liu, *Resource Allocation for Wireless Networks*. Cambridge, U.K.: Cambridge Univ. Press, 2008.

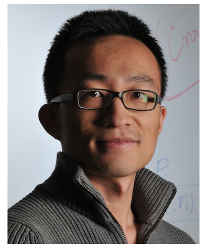
[30] Z. Zhu *et al.*, "Virtual base station pool: Towards a wireless network cloud for radio access networks," in *Proc. ACM CF*, 2011.

[31] S. Sengupta and M. Chatterjee, "Designing auction mechanisms for dynamic spectrum access," *Mobile Netw. Appl.*, vol. 13, no. 5, pp. 498–515, 2008.

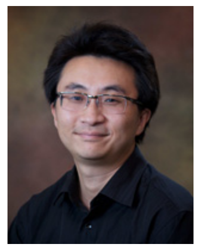
[32] M. N. Tehrani and M. Uysal, "Spectrum trading for non-identical channel allocation in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 10, pp. 5100–5109, Oct. 2013.

[33] Y. Zhu, B. Li, H. Fu, and Z. Li, "Core-selecting secondary spectrum auctions," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 11, pp. 2268–2279, Nov. 2014.

Jing Wang received the B.E. degree from the School of Electronic Information Engineering, Beihang University, Beijing, China, in 2011. He is currently pursuing the Ph.D. degree with the Department of Electrical Engineering and Computer Science, Syracuse University, Syracuse, NY, USA. His research interests include mobile computing and machine learning. He received the Best Paper Award from the 2015 IEEE Global Communications Conference.



Dejun Yang received the B.S. degree in computer science from Peking University, Beijing, China, in 2007, and the Ph.D. degree in computer science from Arizona State University in 2013. He is currently the Ben L. Fryrear Assistant Professor of Computer Science with the Colorado School of Mines. His research interests include economic and optimization approaches to networks, crowdsourcing, smart grid, and security and privacy. He also served as a TPC member for many conferences, including the IEEE INFOCOM, ICC, and GLOBECOM. He received Best Paper Awards at the IEEE GLOBECOM in 2015, the IEEE MASS in 2011, ICC in 2011 and 2012, and the Best Paper Award Runner-up at the IEEE ICNP in 2010.



Jian Tang (M'08–SM'13) received the Ph.D. degree in computer science from Arizona State University in 2006. He is currently an Associate Professor with the Department of Electrical Engineering and Computer Science, Syracuse University. He has authored over 100 papers in premier journals and conferences. His research interests lie in the areas of wireless networking, big data, and cloud computing. He served as a TPC Co-Chair of the 2015 IEEE International Conference on Internet of Things and the 2016 International Conference on Computing, Networking and Communications. He received the NSF CAREER Award in 2009, the 2016 Best Vehicular Electronics Paper Award from the IEEE Vehicular Technology Society, and Best Paper Awards from the 2014 IEEE International Conference on Communications and the 2015 IEEE Global Communications Conference, respectively. He has been an Editor of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS since 2016, the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY since 2010, and the IEEE INTERNET OF THINGS JOURNAL since 2013.

Mustafa Cenk Gursoy received the Ph.D. degree in electrical engineering from Princeton University, Princeton, NJ, USA, in 2004. He is currently an Associate Professor with the Department of Electrical Engineering and Computer Science, Syracuse University. His research interests are in the general areas of wireless communications, information theory, communication networks, and signal processing. He was a recipient of the Gordon Wu Graduate Fellowship from Princeton University between 1999 and 2003. He received the NSF CAREER award in 2006. He received the *EURASIP Journal of Wireless Communications and Networking* Best Paper Award and the UNL College Distinguished Teaching Award. He is currently a member of the editorial boards of IEEE TRANSACTIONS ON GREEN COMMUNICATIONS AND NETWORKING, the IEEE TRANSACTIONS ON COMMUNICATIONS, and the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY. He served as an Editor of the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS between 2010 and 2015 and the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS Series on Green Communications and Networking between 2015 and 2016.