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282

Di Zhang

Virtual Resource-Sharing Mechanisms in Software-Defined and Virtualized Wireless Network

JYVÄSKYLÄN YLIOPISTO

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ABSTRACT

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On the way towards providing scenario-based transmission (enhanced mobile broadband (eMBB), ultra-reliable and low-latency communications (uRLLC), and massive machine type communications (mMTC)) in 5G, the incorporation of software-defined networking (SDN) and wireless network virtualization (WNV) is foreseen to offer such softwarization and service-oriented architecture. This research concentrates on reducing the capital expenses (CapEx) and operation expenses (OpEx) significantly from a radio resource management(RRM) perspective. With this objective, one software-defined and virtualized (SDV) architecture for enabling different-level virtualization is first proposed. The designed wireless virtualization scheme offers the ability to abstract and slice the wireless network by separating the control and data planes in a flexible manner. Second, multiple virtual resource-sharing (VRS) mechanisms for ensuring fairness and competitiveness among mobile operators and providers using auction and contract theories are proposed. With such VRS mechanisms, diverse quality-of-service (QoS) requirements of users (data rate, delay, priority, etc.), profits of conflicting operators and providers, and different system-level objectives (system throughput and energy efficiency) are ensured. To validate our proposed VRS mechanisms, a variety of mathematical demonstrations are conducted with different theoretic approaches (auction and contract theories). The performance of each mechanism is separately evaluated with system level simulations.

Keywords: SDN, Resource Management, WNV, Auction Theory, Contract Theory, VRS, CapEx, OpEx

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ACRONYMS

WNV	Wireless Network Virtualization
SDV	Software-Defined and Virtualized
SDN	Software-Defined Networking
RRM	Radio Resource Management
VRS	Virtual Resource Sharing
CapEx	Capital Expenditures
OpEx	Operational Expenditures
CN	Core Network
RAN	Radio Access Network
RRA	Radio Resource Allocation
InP	Infrastructure Provider
MNO	Mobile Network Operator
MVNO	Mobile Virtual Network Operator
SP	Service Provider
eMBB	Enhanced Mobile Broadband
uRLLC	Ultra-reliable and Low-latency Communications
mMTC	Massive Machine Type Communications
QoS	Quality of Service

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PI Di Zhang, Zheng Chang, Mikhail Zolotukhin and Timo Hämäläinen. Energy Efficient Resource Allocation in Heterogeneous Software-Defined Network: A Reverse Combinatorial Auction Approach. *Proc. of 4th IEEE/CIC International Conference on Communications in China (ICCC'15)*, 2015.

PII Di Zhang, Zheng Chang and Timo Hämäläinen. Reverse Combinatorial Auction-based Resource Allocation in Heterogeneous Software-Defined Network with Infrastructure Sharing. *Proc. of 83rd IEEE Vehicular Technology Conference (VTC'16-Spring)*, 2016.

PIII Di Zhang, Zheng Chang, Fei Richard Yu, Xianfu Chen and Timo Hämäläinen. A Double Auction Mechanism for Virtual Resource Allocation in SDN-based Cellular Network. *Proc. of 27th IEEE Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC'16)*, 2016.

PIV Di Zhang, Zheng Chang, Timo Hämäläinen and Fei Richard Yu. Double Auction Based Multi-Flow Transmission in Software-Defined and Virtualized Wireless Networks. *IEEE Transactions on Wireless Communications, Volume 16, Issue 12, Pages 8390-8404*, 2017.

PV Di Zhang, Zheng Chang, Timo Hämäläinen and Weinan Gao. A Contract-based Resource Allocation Mechanism in Wireless Virtualized Network. *Proc. of 37th IEEE International Conference on Computer Communications (INFOCOM'18)*, 2018.

PVI Zheng Chang, Di Zhang, Timo Hämäläinen, Zhu Han and Tapani Ristaniemi. Incentive Mechanism for Resource Allocation in Wireless Virtualized Networks with Multiple Infrastructure Providers. *Submitted to a journal*, 2018.

1 INTRODUCTION

1.1 Motivation

In the new exciting era of 5G, new communication requirements pose challenges FOR existing networks in terms of technologies and business models. The next-generation mobile network must meet diversified demands (Andrews et al., 2014) including eMBB, uRLLC, and mMTC. As illustrated in Fig. 1, these three categorized scenarios by the international telecommunication union (ITU) separately raise hard-to-implement but necessary QoS requirements: continuously evolved broadband $10Gbps$ for high-definition (HD) videos, virtual reality (VR), and augmented reality (AR); $1ms$ latency for emerging critical applications such as remote surgery and intelligent transportation systems (ITSs); $1million/km^2$ connection for the envisioned 5G internet of things (IoT) scenario with tens of billions of connected devices and sensors. From a network management perspective, the static and hardware-based platform in the existing LTE/LTE-A technology suffers from scalability and flexibility due to the coupled design of control and data planes. Therefore, the existing cellular technologies need to be upgraded to support the envisioned wide range of on-demand services in 5G/Beyond 5G networks. System architecture has been considered as service-based compared to previous generations (Petrov et al., 2018). Wireless network virtualization (WNV) (Wen et al., 2013) has been considered one of the most promising technologies for such network architecture revolution. Using WNV, multiple logical networks can be created on top of a common shared physical infrastructure for addressing the imposed cost, efficiency, and flexibility QoS requirements. Consequently, mobile network operators (MNOs) can significantly save the CapEx and OpEx of both radio access networks (RANs) and core networks (CNs). Furthermore, with the deployment of WNV, more functions can be softwarized and migrated for the installation of new technologies and products in the future, especially for creating industry-specific virtual networks, e.g., drone-assisted vehicular networks, smart healthcare network, etc.

However, while WNV is a promising solution for future service-oriented ar-

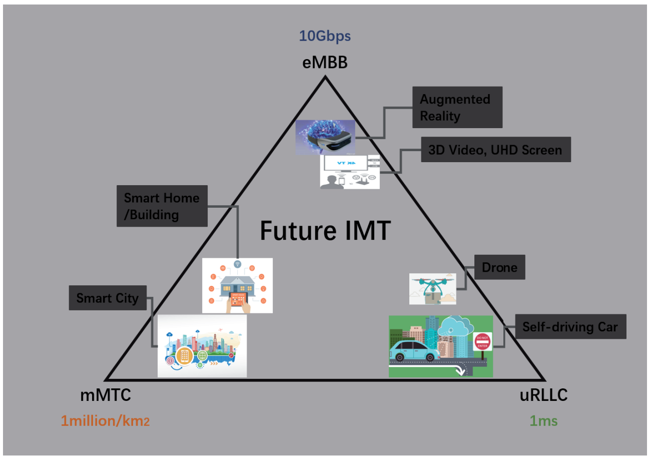

FIGURE 1 Three dimensions of performance improvements with usage scenarios for 2020 and beyond.

chitecture, several significant challenges remain to be addressed before its broad implementation, e.g., how to abstract the physical resources, with which isolation granularity the resource can be shared more efficiently, how to allocate the virtualized resources among the RRM process, how to ensure the minimum handover failure and how to achieve the maximum resource efficiency, etc. Non-technical issues such as government regulations, operator negotiations, and corporation competitiveness are also challenging. In particular, wireless cellular virtualization is significantly different from wired networks, whose bandwidth resource abstraction and isolation process can be done based on hardware.The abstraction and isolation of radio resources in WNV need to consider stochastic fluctuations in the wireless channel quality, which makes the RRM even more challenging. In addition, since vertical industries are very diverse and their requirements are dictated by the service characteristics of the related vertical segment, the standard WNV model for 5G and beyond needs a market model to guarantee benefits for all entities through WNV. These challenges need to be studied carefully with comprehensive research efforts.

Motivated by the important business opportunities introduced by WNV, this research addresses the virtual resource-sharing (VRS) problem, which focuses on investigating suitable enabling technologies to isolate and slice the physical resources into virtual networks, designing efficient radio resource allocation (RRA) mechanisms to accommodate the heterogeneity of the traffic demands and satisfies the end-to-end service requirements, and applying suitable business models to guarantee benefits of all business roles involved in this new service-based wireless network architecture.

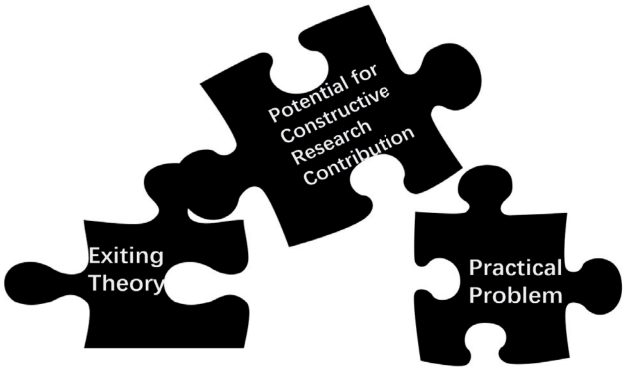

FIGURE 2 The rational of constructive research

1.2 Research Questions and Approach

To tackle the previously mentioned issues, this research attempts to answer the following research questions:

- **RQ1**. How can a virtualized wireless network architecture be designed considering flexibility, compatibility, stability, and scalability to save CapEx and OpEx?
- **RQ2**. How can the diverse traffic demands and requirements be satisfied to enable rapid service provisioning and flexible network operation?
- **RQ3**. How can the heterogeneous radio access technologies (RATs) be accommodated by slicing and allocating the virtualized resources?
- **RQ4**. How can the fairness and benefits of multiple involved business roles (such as infrastructure providers, mobile network operators, and service providers) be guaranteed with conflicting interests by the proposed resource sharing mechanism?

To answer these questions, this research takes advantage of the constructive research approach (CRA) (Dresch et al., 2014), which aims at developing an innovative construction/solution to solve the real-world problem by using existing theoretical knowledge (in Fig. 2). The process of finding scientifically relevant real-world problem, applying suitable theories and obtaining valuable results contributes to not only the particular field of science where the theory is applied, but also the practical problem-related research field. In this research, the problem of finding solutions to reduce the CapEx and OpEx of the 5G wireless cellular network is solved with the help of constructing overall virtual network slicing/sharing framework with SDN technology and economic tools: auction theory and contract theory.

1.3 Research Contributions

The authors' contribution to the included articles is in the development of the entire framework required to find a solution to each problem posed. Such framework involves the exploration of enabling technology, problem formulation, the development of a method for its solution, the evaluation of the proposed mechanism performance, and its comparison with existing analogues. The detailed contribution of the included articles with aforementioned research questions is presented in Table 1 and the structure of the research and included articles is presented in Figure 3.

TABLE 1 The contribution of original research articles to the research questions

Research Questions	Articles
RQ1	**[PI] and [PII]**: The virtualization architecture was designed as the infrastructure level, where multiple infrastructure providers (InPs) can share the resources to reduce CapEx and OpEx by the author. **[PIII] and [PIV]**: The virtualization architecture was designed as the flow level, which is a service-based level and can enable multiple mobile virtual network operators and InPs to further reduce OpEx by switching off low-traffic-load base stations. The detailed virtualization process and properties like scalability and stability were presented in [PIV]. Unfortunately, due to the rapid evolution of enabling technologies, uncertain developing direction of 5G, and limited efforts to implement such platform, the proposed SDV architecture for addressing flexibility and scalability was a proof of concept, which will be extensively developed in our future work.
RQ2	The matching process of offering and demand was solved by formulating the diversity customer service and QoS requirements as variables in the proposed virtual resource-sharing mechanisms by the author. **[PI] and [PII]**: the traffic demand was formulated as the minimum data rate requirement. **[PIII] and [PIV]**: the traffic demand of the end user and providable data rate was formulated as decision variables, where demand was represented by the minimum data rate requirement with the scheduling weight and the offer was represented by the maximum data rate with the usage state weight. **[PV] and [PVI]**: The diversity of user demand was extensively studied, where both user's required content and transmission delay were considered in the formulated contract.
RQ3	The heterogeneous RATs of diverse InPs were considered as constraints with different objectives in the proposed virtual resource-sharing mechanisms by the author. **[PI]**: System throughput maximization was achieved by restricting the maximum allocated power to specific users. **[PII]**: Energy efficiency was enhanced compared to [PI]. **[PIII]**: The heterogeneity of multiple MVNOs and InPs were addressed by different pricing schemes designed for resources. **[PIV]**: Based on [PIII], the heterogeneity was further achieved using the transaction-related cost by considering energy consumption and the relative distance between UE and BS. **[PV] and [PVI]**: The heterogeneourity was naturally existing among multiple InPs when signing contract with MVNOs, where the quality-related transmission cost including the energy consumption pricing mechanism was proposed.
RQ4	**[PI] and [PII]**: Reverse combinatorial auction-based resource-sharing mechanisms, as nature decentralized market mechanisms for ensuring fairness and competitiveness, were proposed to address the competitive behavior of infrastructure providers by the author. The auction process was solved by the winner determination problem. **[PIII] and [PIV]**: Double auction-based resource-sharing mechanisms were proposed to address the hidden information among multiple MVNOs and InPs by the author. By simultaneously considering energy efficiency, cost expense, and diverse QoS requirements, achieved results can stimulate different InPs sharing infrastructure, balance traffic flow and reduce both CapEx and OpEx significantly. **[PV] and [PVI]**: Contract theoretic approaches were proposed to regularize the resource-trading process in WNV with complete and incomplete information separately by the author.

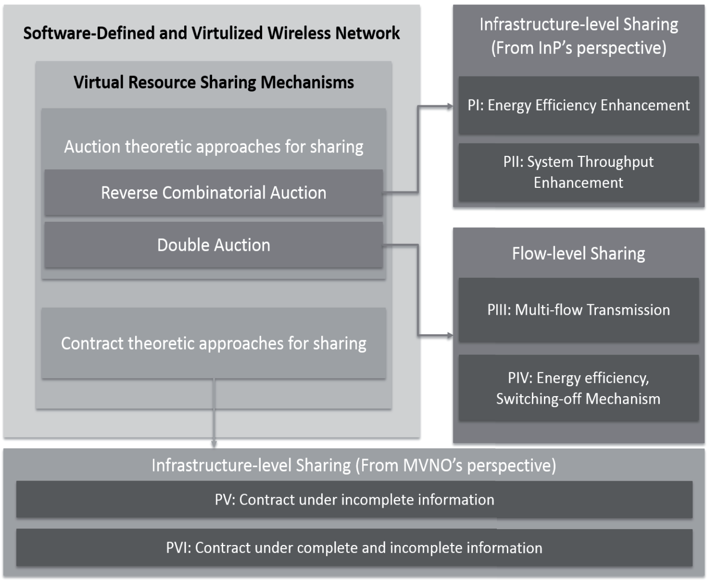

FIGURE 3 The structure of PhD research.

1.4 Organization

The remainder of this thesis is organized as follows:

Chapter 2: This chapter provides the relevant preliminary knowledge for WNV. Basic concepts, business roles, and slicing levels are first explained. Then the applied enabling SDN technology for WNV is briefly presented. Two economic tools: auction theory and contract theory, are then summarized to ensure the business benefits in WNV-involved participants.

Chapter 3: The related works in the area of SDN-enabled WNV are widely surveyed. Auction- and contract-based virtual resource-sharing mechanisms are later presented to explore the effectiveness and research neck bottle of SDN-enabled WNV. At the end of each subsection, shortcomings of the previous work are treated as challenges and and serve as the background of our research.

Chapter 4: Our proposed novel research solutions as well as performance evaluations are presented in this chapter. The research results on the research challenges discussed previously are categorized into three groups: our proposed novel SDV platform, auction-based mechanisms to enhance the spectrum efficiency and the energy efficiency, and contract-based incentive mechanisms to stimulate InPs sharing the infrastructure. Some examples of simulation results of the research work are included as well.

Chapter 5: The chapter presents conclusions and offer directions for future research work.

2 ENABLING TECHNOLOGY AND THEORIES

This chapter focuses on enabling technology and theories employed in the articles included in this research. First, WNV is discussed in greater depth by introducing involved business roles in WNV and virtualization levels. Next, the main enabling technology SDN is introduced with examples. Finally, concepts and properties of two enabling theories, auction theory and contract theory, are presented.

2.1 WNV

WNV can be considered an umbrella term for *wireless access virtualization*, *wireless infrastructure virtualization*, *wireless radio access network virtualization*, and even *wireless core network virtualization*. Similar to wired network virtualization, WNV can be interpreted as the abstraction, isolation, and sharing of wireless access devices among multiple users or user groups with a certain degree of isolation between them (Wen et al., 2013). In this thesis, WNV in cellular networks is extensively researched and applied to reduce CapEx and OpEx in the evolution of network architecture for mobile operators and providers. It is considered the technology for abstracting and isolating physical layer resources (licensed spectrum resources, network infrastructures, backhaul, etc.) into specific virtual networks to realize sharing among multiple operators and providers.

2.1.1 Business Model of Wireless Virtualization

WNV brings to mobile operators the promises of reducing costs, enhancing network flexibility and scalability, and shortening the time-to-market of new applications and services. Two main business models are widely used for describing the relationship among different profit holders in the WNV market. We present these in Fig. 4. When business entities (infrastructure providers, mobile network operators, service providers, etc.) want to participate in the virtualization process, they can choose one of the logical roles according to the system model and business requirements. Generally, the virtualized wireless networks consist of an infrastructure provider (InP) and a mobile network operator (MNO) (Habiba and Hossain, 2018):

- **InPs**, business entities who own or want to share one of the infrastructure resources like network infrastructure (antennas, BSs, backhaul, etc. in radio access network, femto cells, small cells), radio resources (licensed spectrum, backhaul) or both can choose to be InPs. Specially, when an InP only owns radio resources, the virtualization can be defined as spectrum-level slicing. When an InP only owns network infrastructure, the virtualization can be defined as the infrastructure-level. Sometimes, the infrastructure-level includes spectrum allocation. Furthermore, when an InP also own and want to share their core network (CN), the virtualization can be upgraded to network- and flow-level slicing. The four-level virtualization is defined in next subsection.
- **MNOs**, business entities who own subscribers and do not own physical layer resources can choose to be MNOs. MNOs require and lease virtual networks resources from InP/InPs to offer various services for their own subscribers with different QoS requirements..

In this two-level business model, InPs mainly take charge of the virtualization process. They abstract and virtualize their resources into slices and then interact with other InPs and MNOs to manage the virtualized resources. The MNO only utilizes the slices from an InP depending on specific service-level agreements and provides service to the end users without knowing the underlying physical network architecture. Therefore, with this two-level business model, more research attention should be paid to investigate the fairness and competitiveness among InPs. Our research [PI] and [PII] try to answer these problems with auction theory.

With the evolution of SDN in the application of WNV, more involved participants (such as wireless service providers, application or content providers, or business entities who provides the cloud services like C-RAN, IaaS, RaaS, edge computing and etc.) entered into the WNV market and the key WNV business player MNO can be further decoupled into more specialized roles: mobile virtualized network operators (MVNOs) and service providers (SPs):

- **MVNOs**: mobile vitual network operators manage the virtual resource requests from SPs and lease resources from one or multiple InPs according to demand requests. Then, an MVNO uses virtualized resource slices for end users to satisfy its own subscribers' QoS requirements.
- **SPs**: service providers do not have sufficient infrastructure and/or resources to provide wireless services to their subscribed users. They lease or purchase infrastructure and resources from InPs. The accumulated requests from end users are satisfied through MVNOs intermediately.

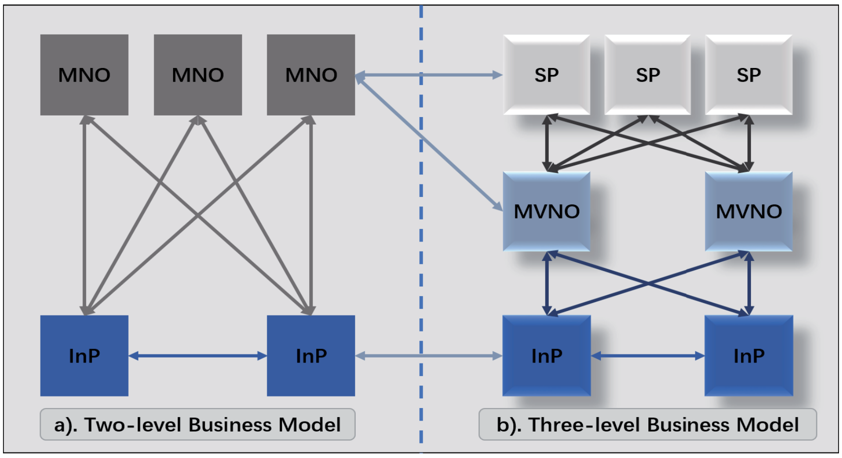

FIGURE 4 Business models of wireless network virtualization. a) Traditional two-level business model; b) Enhanced three-level business model.

In this evolved three-level business model, an MVNO is a virtual entity representing an SP in the virtualization layer who leases resources from one or multiple InPs according to the demand requests received from the SP. In particular, in the two-level business model, an InP plays the central role who directly allocates the physical resources to users of different MNOs according to certain requirements (e.g., pre-determined resource-sharing ratios). In the three-level model, MVNO is also involved in the allocation process, where an InP only responds to an MVNO and the MVNO aggregates demands and allocates resources to end users. In this hierarchical resource allocation mechanism, the MVNO has more flexibility and agility to end users' demands concerning economic benefits. The enhanced three-level business model is also applied in this research: [PIII] and [PIV].

2.1.2 Isolation Granularity

Resource isolation is an essential part in the virtualization process. The level of isolation directly influences the efficiency of resource sharing. Four kinds of virtualization are extensively applied in WNV (Hossain and Hasan, 2015):

- **Spectrum-level slicing**: the entities (InPs) who own the licensed spectrum resources take charge of spectrum-level slicing to achieve spectrum efficiency. They isolate the spectrum through different multiplexing and frequency reuse methods. If the entity also owns infrastructure resources, the spectrum efficiency can be further enhanced by MIMOs, power control, etc. The entities are usually InPs.
- **Infrastructure-level slicing**: the entities (InPs) who own physical layer elements (e.g., RAN, antennas, BSs, CNs, backhauls, etc.) can initiate the infrastructure-level slicing, i.e., the infrastructure can be abstracted, shared and leased among InPs and MNOs/MVNOs. In particular, if some InPs

have spectrum but limited coverage, they can rent infrastructure (e.g., antennas, power allocation,) for a certain area to satisfy the end users.

- **Network-level slicing**: the entities (InPs) who also want share the CN can initiate network-level slicing. This network-level slicing will virtualize the whole network, which includes physical network nodes (e.g., BSs, relays, femto APs), CNs (e.g., mobility management entity (MME), serving gateway (SGW)) and computing modules (e.g., CPU, memory, I/O devices) within a close geographical area. The virtualized network can be viewed as multiple resource-packages for specific MNO/MVNOs based on some criterion (e.g., users link quality, MNVOs' resource requirements, power budget, interference, etc.) to satisfy their own subscribers' demands. Only CN sharing can also be viewed as this level of slicing.
- **Flow-level slicing**: the resource slice in this level of slicing can be defined as the set of virtual resources (e.g., traffic flows) virtualized by InPs and requested by the MNO/MVNOs. The resource slice could be based on specific service-level requirements like the data rate, delay, bandwidth etc. Therefore, this level slicing introduces an additional layer of abstraction and isolation to implement service-level leasing and renting. To this end, flow-level slicing can be seen as one main 5G key technology **end-to-end network slicing**[1], which is expected to be the main component of 5G.

2.2 SDN

SDN is an emerging network architecture where network control is decoupled from forwarding and is directly programmable. It is considered one of the most promising technologies to realize WNV, especially in the evolution of wireless cellular network (Bernardos et al., 2014). As illustrated in Fig. 5, functional elements are aggregated into a **control plane** by decoupling them from a **data plane**, where the data plane is only responsible for forwarding data. With this centralized control, 5G network architecture can be service-based and more dynamic, manageable, cost-effective and adaptable for supporting today's applications, especially eMBB, mMTC and uRLLC scenarios.

There are five key features of SDN-based architecture (Nadeau and Gray, 2013):

- ***Directly Programmable***: By merely leaving the forward function in the data plane, more control functions are decoupled and aggregated within the control plane. Particularly, the BSs only take charge of executing decisions from the control plane through Southbound API for forwarding data. The MME,

[1] The definition of network slicing is still under heavy discussion. There, we define "slice" as an isolation of programmable resources to omimplement network functions and applications through software programs for accommodating individual network functions and applications within each slice without interfering with outer functions and services on the existing slices (Zhang et al., 2017)(Foukas et al., 2017).

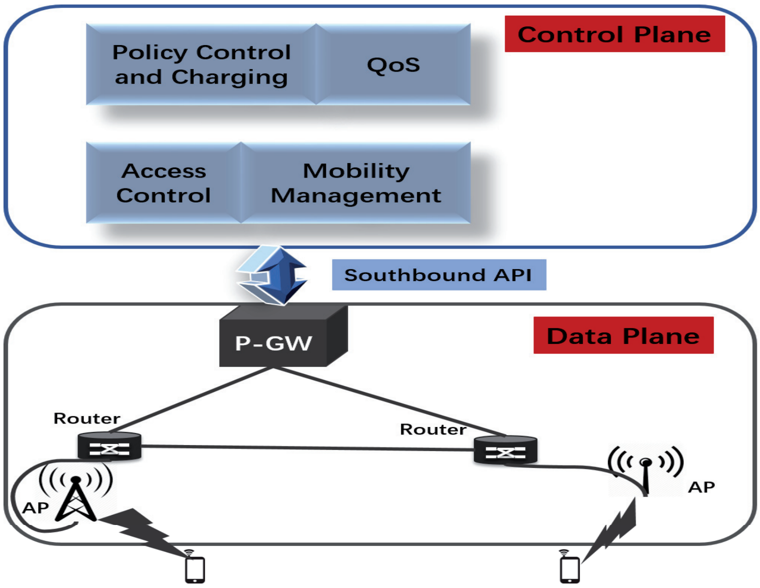

FIGURE 5 A general framework for SDN.

QoS, power control etc. in core network manage the resources and configure BSs for specific service.

- ***Centrally Manageable***: All network-side functions can be centrally managed and controlled. The entity who maintains a global view of the network is defined as the SDN controller. It acts as a single and logical switch for applications, services and policy engines.
- ***Programmatically Configurable***: In the control plane, functions (MME, access control, power control, etc) are packed and opened as Northbound API for interacting among them. Therefore, the SDN ensures dynamic and automatic configuration among diverse functions, which optimizes the whole network in a programming way.
- ***Agile***: With specific interface and configurable functions, the SDN can initiate agilely reaction to different QoS requirements, and dynamically adjust traffic flows to meet changing needs.
- ***Open standards-based and vendor-neutral***: SDN is an open standard-based networking method, which simplifies network design and operation. With this characteristic, it accelerates the development and application, especially in the view of joint development with WNV.

As the control plane is responsible for whole control functions, the most challenging design part is concentrated on the control plane. There are three design methods for implementing the control plane: centralized, hierarchical and decentralized.

- **Centralized**: the initial trials are mainly focusing on this centralized solution, where a single control entity has a global view of the network. Even though the idea behind this simplifies the implementation of the control logic, it has scalability limitations with the increasing network size and more evolved business entities.

- **Decentralized**: the decentralized solutions allow controllers to operate on their local view and they may only exchange synchronization messages to enhance their knowledge. Even though distributed solutions are more suitable for supporting adaptive SDN applications, they are hard to implement in real scenarios because of the uncertain behaviors of vendors and users.
- **Hierarchical**: hierarchical solutions take advantage of both centralized and decentralized solutions, which allow lower-level controllers to make decisions on their own in a more flexible manner. On the other hand, decisions requiring network-wide knowledge can be taken by a logically centralized root controller. This idea is applied in our research.

Therefore, with this decoupled architecture, network operators can write high-level control programs that specify the behavior of an entire network compared with conventional networks, where network operators can only configure some low-level functionality. In this research, we take advantage of this decoupled architecture with a hierarchy control plane.

2.3 Enabling Theories

2.3.1 Auction Theory

Auction theory is a natural choice for addressing the fairness and competitiveness among multiple profit holders, especially in the process of buying and selling commodities or services. No matter how the transaction happens, with different auction mechanisms, the fairness and competitiveness can be ensured. Buyers/Sellers feel free to decide whether to participate the trading or not. To design a suitable auction, a trading market with different profit entities and trading commodities should satisfy the basic terminologies in auction theory. Table 2 concludes basic terminologies and their definition in auction theory. To make concepts clear and understandable, we map the basic terminologies with a general WNV market also.

Generally, different participants (**buyers** and **sellers**) have different **valuations** on specific **commodities**. The process of valuation is defined as **pricing**. Bidders/buyers have the nature of competition and when they decide to participate in the auction, several conditions need to be satisfied. The functions and rules of auction are designed by the **auctioneer**, and the auctioneer can decide to be a non-profit or profit entity.

TABLE 2 Basic terminologies and their relationship with WNV in auction theory

Terminology	Definition	Mapping in wireless cellular, e.g.
Bidder	A bidder is the one who wants to buy commodities in auctions	End users
Seller	A seller owns and wants to sell commodities	Base stations
Commodity/item	An auction commodity/item (also known as an auction commodity) is the object traded between a buyer and a seller	Bandwidth, licenses of spectrum, and time slots in radio resource auctions
Auctioneer	An auctioneer works as an intermediate agent who hosts and directs auction processes	Generally a seller can be an auctioneer itself
Valuation	In general, valuation is the monetary evaluation of assets	Channel quality, data rate, delay
Pricing	The process of an auctioneer making a decision on a price, which indicates the buyer and the seller will make a deal at, is defined as *pricing*, and the price is called *hammer price*	Policy and Charging Rules Function (PCRF) in LTE

2.3.1.1 Classification of Auctions

There are many classifications of auctions. Different classifications can help to apply auction theory in a more efficient manner, especially when the market has specific properties. We offer four kinds of classification here: the ways in which bids are proposed, the method of deciding the hammer price, the bidding side, and the bidding items.

Firstly, based on the way in which bids are proposed, English and Dutch auctions are classified as follows:

– **English auction**: An English auction works as an ascending-bid auction, i.e., the bidding price submitted by buyers will increase monotonically. The auction will terminate when no buyer bids a new higher price. Then, the buyer who offers the highest price finally wins the auction.
– **Dutch auction**: A Dutch auction is a descending-bid auction. The seller firstly sets an initial ceiling price for the commodity and decreases the price over time (e.g., per hour), until the price becomes zero. Once a buyer accepts the current price by placing a bid, the auction terminates. Then the winning buyer pays the final price and receives the commodity.

English and Dutch auction are two conventional auctions, which are extensively used in normal auction markets for allocating one item/commodity (Koutsopoulos and Iosifidis, 2010). In our research work [PI], an English auction is applied as the iterative ascending price auction algorithm.

Secondly, according to the methods to determine the hammer price, the auction can be classified into first-price paying and second-price paying.

– **Blind auction**: also known as first-price sealed-bid auction (FPSB). In this type of auction all bidders simultaneously submit sealed bids so that no bidder knows the bid of any other participant. The highest bidder pays the price they submitted.
– **Vickrey auction**: also known as a second-price sealed-bid auction (SPSB). This is identical to the sealed first-price auction except that the winning bidder pays the second-highest bid rather than his or her own. Vickrey auctions

are the most widely used auction method in wireless communication society (Wang et al., 2017). The classic VCG mechanism is a generalized truthful auction mechanism for multiple units of homogeneous or heterogeneous items that provides a socially optimal solution.

Within this classification, the bidders submit bids once and the auctioneer decides the winner and the hammer price. The Vickrey type of auction is strategically similar to an English auction and gives bidders an incentive to bid their true value. Therefore, we apply the idea of addressing truthful bidding in our research.

Thirdly, according to different sides for submitting bids, auctions can also classified into three categories: seller-side, buyer-side and double-side.

- **Forward auction**: also named seller-side auctions, where buyers compete for the commodities from the seller. It is the mostly common used one.
- **Reverse auction**: also named buyer-side auctions, where roles of sellers and buyers are interchanged i.e. a buyer acts as a seller and a seller acts as a buyer in terms of bidding for a particular item. The sellers compete to obtain business from the buyer.
- **Double auction**: In the double auction, both sellers and buyers submit their asks and bids respectively. Different from the abovementioned two auctions, an independent entity will be an auctioneer to decide the auction commodity allocation scheme and the hammer price, and managing the trading between the buyers and the sellers.

In our research, to address the competitiveness among InPs and emphasize the importance of satisfying user demand, we apply a reverse auction in [PI] and [PII]. A double auction is also used for simulaneously considering the interaction among MVNOs and InPs in [PIII] and [PIV].

Finally, as in some situations, buyers need to buy a basket or a structured combination of heterogeneous commodities. According to the number of bidding items, we have single-item auction and combinatorial auction (Zhu and Hossain, 2016).

- **Single-item auction**: In single-item auctions, the sellers offer a single type of commodity consisting of one or more indivisible units. If there is only one unit available, then the auction is referred to as a single-item single-unit auction. On the other hand, a single-item multiple-unit auction refers to an auction where bidders can request for multiple units of the same item.
- **Combinatorial auction**: also known as a heterogeneous auction, where bidders can bid for arbitrary combinations of items and express their actual preferences over the bundles of items considering the complements and substitutes among items.

Compared to single-item auctions, combinatorial auctions present more challenges concerning the nature of computational complexity, i.e. how to efficiently determine the allocation once the bids have been submitted to the auctioneer. The problem with identifying which set of bids to accept has usually been dubbed the **winner determination problem**. We investigate this kind of auction in our research work [PI]-[PIV].

2.3.1.2 Feasible Conditions of Auctions

An auction mechanism involves designing an algorithm to obtain the allocation outcome along with a pricing rule to determine the payment prices for the participating bidders. The auction mechanism is expected to satisfy the following economic properties:

– **Individual Rationality (IR)**: An auction is individual rational if each player receives a non-negative utility gain. A winning buyer is charged according to his/her bid price, not more than the bid. Similarly, a winning seller gets a maximum reward equivalent to the ask price.
– **Balanced Budget (BB)**: An auction is budget-balanced when the auctioneer collects the payments from the winning buyers and transfers the same amount to respective seller(s). This guarantees that there is no deficit for the auctioneer and that the auctioneer is a non-profit entity. However, when the auctioneer is an profit entity, the BB condition becomes challenging to satisfy. We investigate this in [PIV].
– **Truthfulness (TF)**: An auction mechanism is said to be incentive-compatible or strategy-proof when every bidder gets the maximum utility by submitting his/her true valuation over the item(s). The dominant strategy of truthful bidding ensures that no buyer or seller can improve his/her utility by submitting any non-truthful bid or ask prices.
– **Economic efficiency (EE)**: An allocation in the auction is considered efficient when the sum value of all winning bids is maximized. An auction mechanism is considered computationally efficient if the auction has a polynomial time allocation algorithm. From an economic perspective, an auction is optimal if it maximizes the seller's revenue.

However, it is impossible for a valid auction mechanism to obtain all the aforementioned properties. Typically, for a VCG auction, IR and TF are necessary, and it is also normal that only IR, TF and BB are satisfied for a double auction.

2.3.2 Contract Theory

Contract theory studies the design of agreements that motivate people with conflicting interests to take mutually beneficial actions. It guides us in structuring arrangements between employers and employees. Generally speaking, the performance of employees tends to be better when they work harder, and the probability of a bad performance will be lower if employees have higher levels of dedication and focus on the work. In contrast, on the other hand, if an employee's compensation is independent of his or her performance, the employee will be less likely to put efforts into the work (Zhang et al., 2017b). Therefore, the design of incentive mechanisms plays an important role in addressing the problem of employee incentives.

2.3.2.1 Classification of Contracts

In essence, contract theory is about giving each party the right incentives or motivations to work effectively together. However, there is an informational gap between employer(s) and employee(s), which usually refers to the fact that the employer/seller(s) does not know exactly the characteristics of the employee /buyer(s). According to the time when the employer and the employee sign the agreement, contracts can be classified into adverse selection and moral hazard.

- **Adverse Selection**: Adverse selection means that the employer considers information gap/asymmetry before designing the incentive mechanisms for employees, i.e., the information about some relevant characteristics of the employees, such as their distaste for certain tasks and their level of competence/ productivity, are hidden from the employer. Besides, employees may not reveal the state truthfully. A contract in these circumstances tries to elicit employees' information. Usually, the adverse selection problem can be addressed by revelation principle, where the employer can offer multiple target-reward employment contracts (t, r) for employees of different skill levels, where t is the employee's outcome wanted by the employer, and r is the reward paid to the employee by the employer if the given target is achieved. The outcome can be the duration of work time, a required performance, or some other outcomes that the employer wants from the employee. It is the most widely used model in wireless communication.
- **Moral Hazard**: In contrast to adverse selection, the informational asymmetries in moral hazard arise after the contract has been signed, which usually refers to situations in which the employee's actions are hidden from the employer, e.g., whether they work or not, how hard they work, how careful they are, etc. Moreover, employees may not deliver on their promises due to imperfect monitoring. In contrast to target-reward incentive mechanisms in adverse selection, a menu of action-reward bundles (a, r) are offered by employers in moral hazard, where a is the action or effort exerted by the employee after being hired, and r is also the reward paid to the employee by the employer. However, as hard work cannot always be observed properly, this performance-based pay method has hardly been applied in wireless networks to date.

To this end, by using contract theory based models, the employer/seller(s) can overcome this asymmetric information and incentivize its employee/buyer(s) efficiently by offering a contract that includes a given performance/target and a corresponding reward/price. The complete information scenario, where the target/performance is known to the employer, is always used as as a benchmark to evaluate the performance of the proposed contracts under incomplete information.

2.3.2.2 Feasible Conditions of Contracts

In contract theory, the solution we need to obtain is a menu of contracts for employee by employer. The problem is typically formulated as objective-constraints optimization problem, where the objective is to maximize the employer's payoff or utility, and the constraints are incentive compatibility (IC) and individual rationality (IR), which can protect employee's benefit by agreeing the contract.

– **Incentive compatibility (IC)**: IC constraint ensures that employee's expected payoff is maximized when signing in the contract.
– **Individual rationality (IR)**: IR constraint ensures that the employee's payoff under this contract is larger than or equal to its reservation payoff when not participating.

IC and IR are two necessary conditions to guarantee the effectiveness of a contract. Other conditions for helping achieve an optimal contract like monotonicity, local downward incentive constraints (LDICs) and local upward incentive constraints (LUICs) can be deduced based on IC, IR and other problem-specific constraints.

2.4 Summary

This chapter introduced related concepts, enabling technologies and theories in wireless network virtualization. Specifically, the terminology, classification and feasible conditions of both auctions and contracts were also included.

3 RELATED WORK

The related works in the area of SDN-enabled WNV are widely surveyed. Auction and contract-based virtual resource-sharing mechanisms are later presented to explore the effectiveness and research neck bottle of SDN-enabled WNV. At the end of each subsection, shortcomings of the previous work are treated as challenges and and serve as the background of our research.

3.1 Related Work on SDN-enabled WNV architecture

The current architecture of wireless cellular networks is suboptimal for managing the limited spectrum, allocating radio resources, implementing handover mechanisms, managing interference, and performing efficient load balancing between cells. SDN's decoupled nature sheds more light on catering to these traditionally hard-to implement but desired features (Kreutz et al., 2015). CN and RAN are two primary components in a cellular network, where RAN is responsible for implementing a RAT to build a connection between mobile device and CN. CN is always an important role in the evolution of cellular networks. Every generation has its own way for defining CN, e.g., 2G had mobile switching centers (MSC), home location registers (HLR) and visitor location registers (VLR), 3G had added IP multimedia system (IMS) and 4G brought the mobility management entity (MME) and packet data gateways (PGW). As 5G will be service-oriented and softwarization, these hardware-based CN elements are all viewed as functions, which can be virtualized. To decouple these functions into programmable data and control planes, significant efforts have been made to virtualize the CN and RAN. Table 3 summarizes the SDN-based virtualization for cellular networks. The solutions target RAN, CN, or both of them as virtualization components while designing a software defined architecture with a decoupled controller.

– **Virtualization of CN**: Generally speaking, CN virtualization can significantly save MNOs' capital expenses when coping with evolution and maintenance of next-generation cellular network. Therefore, the virtualization

TABLE 3 The comparison of SDN-enabled virtualization platform

Year	Architecture	Virtualization	Main Features
2010	OpenRoads (Yap et al., 2010)	RAN and CN	Multi-technology and evolution
2012	OpenRadio (Bansal et al., 2012)	RAN	Protocol evolution
	CellSDN (Li et al., 2012)	RAN and CN	Scalability improvement
2013	CROWD (Ali-Ahmad et al., 2013)	RAN	Throughput enhancement and energy efficiency
	OpenRAN (Yang et al., 2013)	RAN	Heterogeneous accessing
	SoftCell (Jin et al., 2013)	CN	Scalability improvement
	SoftRAN (Gudipati et al., 2013)	RAN	Resource allocation
2014	SoftMobile (Chen et al., 2014)	CN	Resource allocation
	CMaaS (Yazıcı et al., 2014)	RAN	Hierarchical decomposition of controllers
	SDWN (Bernardos et al., 2014)	RAN	QoE provisioning based virtualization
2015	SoftAir (Akyildiz et al., 2015)	RAN and CN	Scalable 5G architecture
	MyNET (Zhang et al., 2015)	RAN and CN	Content delivery

of CN is mainly focused on software-defined core devices. (Nguyen et al., 2017) providing a comprehensive survey of state-of-the-art research work on SDN/NFV-based mobile packet CN architecture. SoftCell (Jin et al., 2013) is a classic SDN-based control framework to coordinate inflexible and expensive equipments. SoftCell applied the design principles of SDN to re-design the control plane of mobile CNs. It proposed a single controller to govern the control plane of the whole core network. The main purpose of SoftCell is to improve the scalability and the flexibility of mobile CNs. By orchestrating the forwarding tables of switches in CNs, traffic flows traversing on a given path are controlled according to service policies, and thus is capable of distributing flows among packet processing middleboxes for load balancing and scalability. To improve scalability, it moves the fine-grained packet classification from previously a single place at the packet gateway (P-GW) to edge switches located in base stations.

– **Virtualization of RAN**: The majority work of virtualization has been done on RAN side. SoftRAN (Gudipati et al., 2013) was proposed to redefine the radio access network within LTE infrastructure by abstracting a RAN into a big virtual base station. With a centralized software defined control plane, it takes advantage of full knowledge of the network and allows operators to improve and optimize algorithms for better handovers, fine-grained control of transmit powers, resource block allocation, among other management tasks. Similarly, to cooperate with heterogeneous accessing technologies, OpenRAN (Yang et al., 2013) proposed a complete virtualization and programmability platform, which makes RAN more open, controllable, flexible and evolvable. Operator service-level virtualization was performed at the application modules to separate protocol specific flows. SDWN (Bernardos et al., 2014) was proposed as one kind of dynamic virtualization. Its main idea is taking current network states and reactions into consideration to enhance network performance. Besides, QoS and quality of experience (QoE) experience were also improved through dynamic traffic configuration and RAN programmability.
– **Virtualization of CN and RAN**: OpenRoads (Yap et al., 2010), as one of the first examples, was proposed to offer a seamless mobility management platform among different accessing technologies (LTE, WiFi or WiMax) ge-

ographically. By supporting co-located technology, OpenRoads can obviously increase the network capacity and coverage range. CellSDN (Li et al., 2012) deployed a network operating system to abstract the control functions from both accessing and forwarding devices. To meet the demands for fast and frequent updates, it introduced a local agent to make the real-time decision. To further enhance the network flexibility, SoftAir (Akyildiz et al., 2015) realized the physical-, MAC-, and network-layer function cloudification for RAN and improved the scalability of CN by leveraging high-performance controllers and optimized network management schemes.

Different from the one-controller SDN-based virtualization platform mentioned above, CROWD (Ali-Ahmad et al., 2013), CMaaS (Yazıcı et al., 2014), and MyNet (Zhang et al., 2015) were proposed as hierarchical controller deployment platforms, which can improve the flexibility and scalability of controlling algorithms. CROWD was designed for supporting efficient mobility management and interference elimination in dense cellular networks. The dynamic two-tier SDN controller hierarchy can be adapted to address RAN issues such as control overhead and high operational costs, where local controllers can be used to make fast and fine-grained decisions, while regional/global controllers can have a broader, coarser grained scope, i.e., that take slower but more global decisions. CMaaS consists of a four-layer controller hierarchy, where control is distributed such that a lower-layer controller's function is constrained by the upper-layer decisions. At the same time, the upper layers acquire the network state from underlying controllers to collect a global view and make control decisions. MyNet proposed a service-oriented virtual network auto-creation based architecture to enable service customized networks, where customers can also actively define, manage, and even operate their virtual networks.

As we can see, there is a softwarization trend in the evolution of wireless cellular network architecture. With the experience of virtualizing RAN and CN, 5G aims at offering a new architecture approach, which enables a flexible Network as a Service (NaaS) solution. We intend to achieve this by introducing multi-provider SDN-based virtualization architecture, where network and service performance can be further enhanced through a self-adapting architecture. Techniques like multi-flow transmission (Zhang et al., 2016) and turning off idle BS (Zhang et al., 2017) can be considered to support busy-hour traffic demand or energy optimization. The detailed platform is introduced in Section 4.1.

3.2 Related Work on Auction-based VRS Mechanisms

The trading of network infrastructure and radio resources can be modeled by taking advantage of microeconomic theory, among which auction models serve as a first choice to formulate economic transactions between conflicting parties and to design resource provisioning and pricing schemes for ensuring fairness. Auction is not only a useful tool to model interactions among the interested buyers and sellers, but also a good framework to characterize the participants (e.g., InPs, MVNOs and SPs) in WNV.

In the wireless cellular network market, auction theory was first extensively used in the secondary spectrum trading market to enhance the efficiency of limited spectrum resources (Chun and La, 2009)(Teng et al., 2011)(Gao et al., 2012)(Han and Ansari, 2013). For instance, dynamic spectrum sharing with multiple sellers and multiple buyers as a noncooperative game was investigated in (Chun and La, 2009), where the interaction among homogeneous spectrum buyers and the existence of a symmetric mixed-strategy Nash equilibrium (SMSNE) were considered. The proposed profit-sharing scheme can achieve any payoff vector in the non-empty core of the cooperative game while satisfying two desirable properties (IR) and (IC). Similarly, additional constraints such as variance of channels, transmission forecasting and afore trading histories were considered in (Teng et al., 2011). In (Gao et al., 2012), an integrated contract and auction scheme was proposed, where the problem of how the primary spectrum owner should allocate his/her idle spectrums in a future period among the guaranteed contract users and the spot market users (and charge) to maximize his overall profit was fully analized. Spectrum efficiency associated with power allocation was further considered in (Han and Ansari, 2013), which exploited an auction-based decentralized mechanism to enable the cooperation between primary base stations and the secondary base stations.

By considering the ensured fairness and effectiveness of spectrum trading, combinatorial auction, as a kind of auction in which the auctioneer invites bids on combinations of items rather than on single items (such as spectrum in aforementioned conventional auctions) was later applied to cloud computing (Zaman and Grosu, 2013)(Xu et al., 2014)(Lee et al., 2015)(Prasad et al., 2016)(Zhang et al., 2017) and Device-to-Device (D2D) underlay communication systems (Xu et al., 2012)(Xu et al., 2013)(Liu and Wang, 2014)(Wang et al., 2015)(Wei et al., 2016). For instance, a dynamic virtual machine (VM) provisioning auction mechanism was designed in (Zaman and Grosu, 2013). However, it did not take into account the user's demand. On the contrary, (Xu et al., 2014) proposed an online auction by considering dynamic behaviors of users and QoS requirements and (Lee et al., 2015) further enhanced resource efficiency and profit satisfaction by grouping cloud users with similar interest. The authors in (Prasad et al., 2016) analyzed this from a double-sided perspective, where cloud providers can submit bids containing price, QoS and their offered sets of resources. The resulting double-combinatorial auction enhanced the scalability of the system. (Zhang et al., 2017) further applied combinatorial auctions in the mobile edge computing market. D2D communication underlaying cellular network was expected to bring significant benefits for resource utilization and cellular coverage. However, the resource allocation and power control needs elaborate coordination, otherwise it may cause severe interference between D2D user equipment and cellular user equipment. The authors in (Xu et al., 2012) and (Xu et al., 2013) improved system throughput by a reverse iterative combinatorial auction and (Liu and Wang, 2014)(Wang et al., 2015) enhanced energy efficiency with different flexible power control methods. (Wei et al., 2016) simultaneously addressed system throughput and energy consumption with a reverse combinatorial auction mechanism, which significantly elevated system capacity, saved energy and improved resource utilization.

Compared to a single-sided auction, double auction a more useful tool to clear marker with multiple buyers and sellers under incomplete information, double auction was extensively applied to mobile data offloading market with heterogeneous RATs underlay systems (Iosifidis et al., 2015)(Bousia et al., 2016) (Zheng et al., 2015)(Cao et al., 2015b)(Sun et al., 2016). In particular, a Walrasian auction scheme was proposed to alleviate the cellular congestion and enhance user quality of service (QoS) without requiring costly and time-consuming infrastructure investments (Iosifidis et al., 2015). Considering information asymmetry, the proposed scheme did not require full information about the mobile network operators and holders of access points and created non-negative revenue for the market broker. The authors of (Bousia et al., 2016) proposed a novel market approach to foster the opportunistic utilization of the unexploited small cells' capacity, where the MNOs, instead of requesting the maximum capacity to meet their highest traffic expectations, offer a set of bids requesting different resources from the third-party small cells at lower costs. In (Zheng et al., 2015), an open market of cloud bandwidth reservation was considered, in which cloud providers offer bandwidth reservation services to cloud tenants, especially online streaming service providers, who have strict requirements on the amount of bandwidth to guarantee their QoS. STrategy-proof double Auctions (STAR) can ensure good performance in terms of social welfare, cloud bandwidth utilization, and tenant satisfaction ratio. While the authors in (Cao et al., 2015b) investigated this problem with an energy-efficiency perspective, where users helped each other's transmissions to an access point in multi-user cooperative environment. An iterative double-auction game was used to model the interaction among the users and the access point. In each iteration of this auction game, the users first submitted bids for buying other users' power and asks for selling users' own power, and then, the access point determined the power allocation based on users' bids and asks. To address spectrum inefficiency, heterogeneity and varying channel situation, the authors in (Sun et al., 2016) proposed a novel overlapping coalition formation-based double auction mechanism (VERACITY). A dynamic and iterative coalition formation algorithm to jointly consider spectrum allocation and pricing was later applied and proved to satisfy the economic properties in terms of truthfulness, individual rationality, ex-budget balance and economic efficiency in the dynamic grouping progress.

In WNV, given the successful trials in spectrum trading, cloud computing and offloading market with heterogeneous RATs coexistence, initial trials with auction theory were attempted by (Fu and Kozat, 2010)(Zaheer et al., 2010)(Chen et al., 2012)(Lv et al., 2012) in spectrum-level sharing WNV. By considering the characteristics of inherent network architecture and conflicting interest among multiple InPs, MVNOs and SPs, (Cao et al., 2015a)(Ahmadi et al., 2016)(Zhu and Hossain, 2016) (Gu et al., 2017) investigated infrastructure-level resource-sharing schemes, and (Jarray and Karmouch, 2015)(Zhang et al., 2015)(Esposito et al., 2016)(Obadia et al., 2016)(Zhang et al., 2017a) further analysed network-level slicing mechanisms. Table 4 presents a comparison among existing auction-based virtualization models in terms of auction classification, virtualization level, objective, and economic properties.

TABLE 4 Summary of auction-based business models for WNV

Virtualization Level	**Ref.**	**Research Focus**	**Auction Model**	**Auction Type**
Spectrum-level	(Fu and Kozat, 2010)	Stochastic game for spectrum management	SS-SI	Conventional
	(Zaheer et al., 2010)	On-demand spectrum contracting	MS-MI	Double
	(Chen et al., 2012)	Bandwidth reuse in Bayesian setting	SS-SI	Conventional
	(Lv et al., 2012)	Bandwidth allocation	SS-SI	Conventional
	(Gao et al., 2016)	RB allocation	SS-SI	Conventional
	(Wang et al., 2017)	Fair pricing and resource allocation for RaaS	MS-MI	Double
Infrastructure-level	(Cao et al., 2015a)	Power allocation in SPs	MS-SI	RC
	(Ahmadi et al., 2016)	Massive MIMO spatial stream allocation	SS-SI	Conventional
	(Zhu and Hossain, 2016)	Hierarchical allocation of Spectrum, power and antenna	MS-MI	Double
	(Gu et al., 2017)	C-RAN resource sharing	SS-MI	Combinatorial
Network-level	(Jarray and Karmouch, 2015)	VN embedding	SS-SI	Conventional
	(Zhang et al., 2015)	Online VM allocation	MS-MI	Double
	(Esposito et al., 2016)	VN embedding	MS-MI	Double
	(Obadia et al., 2016)	Dynamic provisioning of VNF service chain (CPU, memory and Bandwidth)	SS-MI	Combinatorial
	(Zhang et al., 2017a)	Dynamic provisioning of VNF service chain (CPU, memory and Bandwidth)	MS-MI	Double

(SS=**S**ingle **S**eller, MS=**M**utile **S**eller, SI=**S**ingle **I**tem, MI=**M**utile **I**tems, RC=**R**everse **C**ombinatorial)

At the spectrum-level, the varying channel and propagation characteristics are the main challenges to the fair and efficient allocation of resources in wireless networks. The auction-based resource allocation mechanism by considering the stochastic varying channels in wireless environment was modeled as a stochastic game in (Fu and Kozat, 2010), where the InP and the SPs interact with each other to exchange traffic information and the resources were allocated dynamically over the auction time slots. The authors of (Zaheer et al., 2010) presented a two-stage Vickrey auction for the on-demand allocation of heterogeneous commodities. As the estimated price from the last round of auction was was local information, it may not be accurate. A Q-learning algorithm can be applied to estimate the price more accurately in a dynamic manner. Such a VCG auction-based virtualization model was presented in (Lv et al., 2012) that incorporated the Q-learning algorithm to determine SPs' optimal bidding strategies. Moreover, the role of SPs can be extended by allowing them to lease their idle resources to other SPs as a virtual InP. This will increase SPs' profit. An auction-based mechanism in (Chen et al., 2012) was designed for such a scenario with the objective of maximizing the resource utilization and achieving additional revenue. Another

VCG-based auction model was considered in (Gao et al., 2016) which prioritized the MVNOs based on their users' QoS requirements and assigned the available RBs one-by-one to the MVNOs accordingly. Similarly, (Gu et al., 2017) further extended the on-demand fair QoS provisioning into cloud SPs in which the radio-as-a-service (RaaS) model was presented.

At the infrastructure-level, a power allocation mechanism for virtualized wireless networks was presented in (Cao et al., 2015a), where the InP virtualized the available power units for sharing with multiple SPs. A two-stage game was formulated based on the sequential auction and Stackelberg game. The authors of (Zhang et al., 2015) further virtualized the physical resources of a massive MIMO antenna system into spatial streams and rented them to MVNOs, within which an auction-time block based on spatial multiplexing was considered. Similarly, (Zhu and Hossain, 2016) considered a massive MIMO-enabled cellular network by using a hierarchical auction mechanism, where the resources were allocated in two stages: InP to MVNOs and then MVNOs to users. (Gu et al., 2017) presented an online auction model in which the Cloud-RAN resources were shared among mobile operators through virtualization. This VCG-based mechanism was solved by WDP with linear programming relaxation and taking the fractional objective value of the social welfare.

At the network-level, the virtualization technique is mainly addressed with network function virtualization (NFV), which allows network operator to abstract not only the physical resources but also the wireless services and network functionalities. In such NFV-enabled network service chaining model, a continuous chain of network functions is virtualized as virtual network functions (VNFs). The network service chaining is designed to provide high QoS to the internet of things (IoT) devices. An online auction was developed in (Jarray and Karmouch, 2015), which enabled the InP to perform the embedding technique by periodically selecting the virtual network (VN) requests that maximize the profits. On the contrary, SP-hosted online auction in (Zhang et al., 2015) considered the stochastic arrival of users' bids and allocated VNF service chains based on the primal-dual framework. An iterative online auction with a price learning algorithm was designed as well. While the authors in (Esposito et al., 2016) periodically considered a consensus-based distributed auction for VN embedding, where during each round, bidders exchange bids with neighboring physical bidder nodes and then VNs are mapped to virtual links according to their agreement policies. (Obadia et al., 2016) and (Zhang et al., 2017a) addressed the dynamic provisioning of the VNF service chain with different pricing schemes, objectives and auction models.

As we can see, all the aforementioned works merely focused on spectrum-, infrastructure-, and network levels. Flow-level sharing/slicing is a new trend in the WNV and there are many open issues such as resource allocation, mobility management, etc. on this research direction.

3.3 Related Work on Contract Theoretic Wireless Networking

Contract theory is proved to be an efficient tool by (Bolton and Dewatripont, 2005) in dealing with asymmetric information between employer seller(s) and employee/buyer(s) by introducing cooperation. In WNV, the employer/seller(s) and employee/buyer(s) can have different roles depending on the scenario under consideration. Thus, there is a considerable potential to utilize the ideas, methods, and models of contract theory to design efficient wireless network mechanisms, especially in designing efficient resource pricing schemes for WNV.

Similar to auction theory, contract theoretic framework within cellular networks was also first applied in the secondary spectrum trading market (Kasbekar et al., 2010)(Gao et al., 2011)(Sheng and Liu, 2014)(Duan et al., 2014). In particular, a structured spectrum market in (Kasbekar et al., 2010) with two basic types of spectrum contracts was proposed: one type was long-term guaranteed-bandwidth contracts and the other was short-term opportunistic-access contracts. The mechanism was proved to help attain desired flexibilities and trade-offs in terms of service quality, spectrum usage efficiency and pricing. The authors of (Gao et al., 2011) designed a monopolist-dominated quality-price contract, which was offered by the primary owner and contained a set of quality-price combinations each intended for a consumer type. An optimal contract with both discrete- and continuous-consumer-type models was derived later to maximize the utility of the primary owner. This systematic analysis and modeling method affected subsequent works: (Sheng and Liu, 2014) further took different communication needs and tolerance for the channel uncertainty into consideration as customers' private information, and (Duan et al., 2014) further analyzed scenarios under both weakly and strongly information asymmetry. Contract theoretic incentive mechanisms on spectrum trading continuously gain research attention with the evolution of wireless mobile network architecture (Kordali and Cottis, 2015)(Ma et al., 2016)(Nguyen et al., 2016)(Zhang et al., 2017c). For instance, a bandwidth-price contract in (Kordali and Cottis, 2015) allowed secondary users to employ hybrid access models, i.e., bandwidth can be employed either by opportunistic spectrum access or exclusive spectrum access of vacant frequency bands leased for exclusive usage. A contract-based cooperative spectrum sharing mechanism to exploit transmission opportunities for device-to-device (D2D) links was proposed in (Ma et al., 2016), where the cooperative relaying scheme can maximize the data rate of the D2D links without deteriorating the performance of the cellular links. Efficient trading of subcarriers under incomplete information in WNV was analyzed as a contract in (Nguyen et al., 2016).

By introducing small-cell underlay communications, contract theory was gaining increasingly research interest both from academic and industry society. For the D2D underlay communication systems, (Zhang et al., 2015) introduced effective contract-based incentive mechanisms that can encourage users to participate in content sharing to offload cellular traffic through D2D links. Delayed traffic offloading, as a promising paradigm to alleviate the cellular network congestion caused by explosive traffic demands, was analyzed in (Li et al., 2016) and simultaneously an incentive mechanism to motivate users to leverage their delay and price sensitivity in exchange for service cost was proposed. For the information-centric network, a small cell-assisted caching incentive mechanism is proposed by (Liu et al., 2017) to further reduce transmission delay and release the traffic pressure over backhaul channels. (Asheralieva and Miyanaga, 2017) structured the contract by making user association a reward. By considering imperfect channel state information, inter-cell interference can be mitigated in the heterogeneous wireless network.

Among all the abovementioned research directions, contract-based new business models play an increasingly important role in the evolution toward 5G, especially in WNV. The new architecture redefined traditional involved players, such as InPs, MNOs and SPs, and was attracting new players like vertical industries to realize 5G communication and beyond. (Nguyen et al., 2016) improved network operators' profit by leasing physical resources (subcarriers) to SPs. The optimal lease-contract was designed for attracting target-type SPs with a quality-based pricing mechanism. Since efficient and flexible resource allocation techniques are required to dynamically allocate the resources for the users associated with different MVNOs, InPs should offer service-based contracts for ensuring fairness among MVNOs. This problem was addressed by (Ho et al., 2017) with a two-stage Stackelberg game where the InP wants to maximize its revenue by leasing the infrastructure to the MVNOs while meeting certain contract agreements and MVNOs want to serve their users with the best performance and want to pay the minimum to InPs. Similarly, (Kazmi et al., 2018) applied a hierarchical matching game-based scheme with contracts, where the high-level matching problem (the InPs acts as the vendor and the MVNOs act as the buyer.) was solved with contracts and low-level matching was formulated as a Stackelberg game.

As we can see, the application of contract theory in WNV is a new trend for resource allocation in 5G and it will accelerate the normalization of WNV when analyzing the interaction and conflicting interest among multiple virtualized players. To this end, there are still many open issues and significant research work to be done in the future.

3.4 Summary

The related work in the area of WNV was widely reviewed from three perspectives: SDN-enabled wireless network virtualization architecture, auction-based VRS mechanisms and contract theoretic approaches on wireless networking. The shortcomings of previous work were summarized and treated as open issues.

4 RESEARCH RESULTS

This chapter presents an overview of the results, research contributions and authors' contribution to the included articles. First, the SDN-enabled WNV platform applied throughout this research is overviewed. Then the virtual resource allocation mechanisms with different theories are divided into sections according to different business roles' perspective, which helps to reflect the contribution of the proposed mechanisms in a more comprehensive fashion.

4.1 Software-Defined and Virtualized Wireless Network Platform

An SDN-enabled wireless virtualized network architecture was proposed in this research, which continuously and chronologically improved. The detailed process for achieving this architecture is defined in [PVI]. This architecture is labeled **s**oftware-**d**efined and **v**irtualized (SDV) architecture, which offers the ability to abstract and slice the wireless network by separating the control and data planes in RAN and CN simultaneously. The SDV controller acts as the hypervisor to host the network virtualization on a programmable platform. The hypervisor uses a priori knowledge about wireless links and traffic status, users' QoS requirements and other service-level agreements among InPs and MVNOs. Therefore, the auction-based algorithms and contract-based algorithms for virtualization can run in SDN controllers.

4.1.1 SDV Architecture

In our proposed SDV architecture, by considering the essence of competition among providers and operators, three logical roles can be identified after virtualization.

– **MVNOs** are *buyers*, who lease the virtualized network resources from InPs based on their subscribed users' demand. SPs accumulate the users' demand and service requirements and forward the requests to the MVNOs.

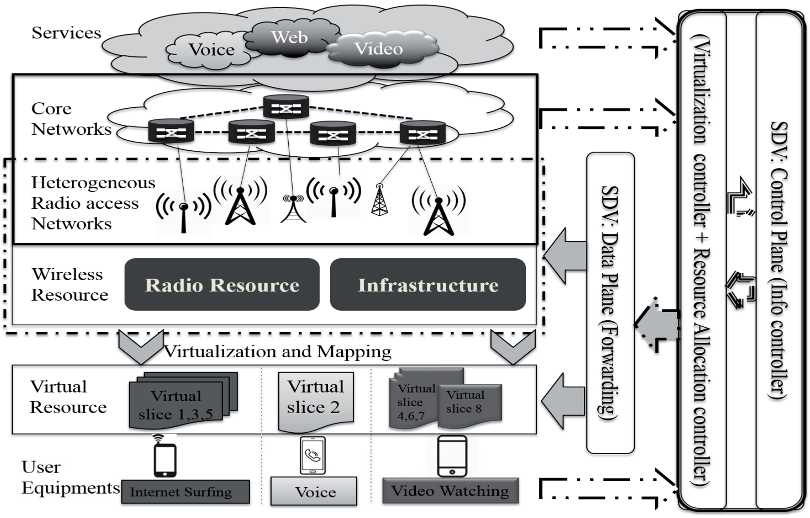

FIGURE 6 The SDV architecture

An MVNO is a virtual entity representing an SP in the virtualization layer who leases resources from one or multiple InPs according to the demand requests received from the SP. For simplicity, MVNOs and SPs represent the same entity.

- **InPs** are *sellers*, who own the physical wireless networks, including radio resources (licensed spectrum) and BSs, and offer a connection with MVNOs based on the BSs' supply. The resources can be virtualized and sliced into different levels: infrastructure-level and flow-level, according to the system requirements.
- **SDN controllers** manage the whole virtualization process including signalling, forwarding, matching and pricing. With different control and optimization algorithms installed, SDN controllers can be defined as specific controllers with specific functions.

With the decoupled nature of SDN, the data and control planes are defined as follows:

- **Data Plane**: a data plane is responsible for the transmission of user traffic via virtual networks. Wireless resources, including the radio resource and infrastructures, are sliced based on the instructions signalled by the Virtualization controller.
- **Control Plane**: a control plane is designed by considering the hierarchical virtualization control idea ("local"and "regional") (Nadeau and Gray, 2013): The SDV regional controller is a logically centralized entity that executes long-term optimizations and the SDV local controller, which runs short-term optimizations. Different controllers can take charge of different functions and they can communicate through special interface among them.

Algorithm 1 Virtualization process in the proposed SDV architecture

1: **Initialization:**

- *Information Collection*: Info controller collects background network status, potential participating InPs, MVNOs and their corresponding QoS requirements, such as minimum demands and maximum supplies. Virtualization-level is defined accordingly.
- *Virtual Slice (**VS**) definition*: Virtualization controller defines VS properties (e.g., time length, data rate, power-level or priority) for each **VS**, based on the pre-agreements with InPs.
- *Slicing*: Virtualization controller generates certain number of virtual VSs for InPs.

2: **Scheduling:**

- *Resource allocation*: The *SDV controller* allocates an appropriate number of VSs to each MVNO based on their QoS requirements (e.g., bandwidth, data rate, scheduling order, etc).
- *Matching*: InPs transmit physical resources (e.g., BS, radio resource) to each MVNO through data plane according to SDV controller's allocation results. MVNOs convert the properties of each VSs to specific QoS requirements and prepares the physical resources for each user.

3: **Pricing:** SDV controller charges suitable prices from InPs and MVNOs.

FIGURE 7 The algorithm for wireless vitrulization

There are many SDV controllers. In the designed control plane, we list three main controllers:

1. ***Virtualization controller*** creates the virtual slice by dynamically and flexibly slicing the infrastructure and radio resources according to the decision made by the RA controller to achieve global optimized resource utilization. All virtual slices are independent, and there is no interference or conflict between them.

2. ***Info controller*** captures and updates the information of services requirements, network resources, and UEs. The state information is then transmitted to the necessary controllers, such as the RA controller, which can be helpful in properly allocating the infrastructure and radio resources.

3. ***Resource Allocation (RA) controller*** runs the resource allocation algorithms. It captures the demands and supplies information from the Info controller, and forwards the decisions to the Virtualization controller.

Consequently, SDV can match resources with UEs' heterogeneous QoS requirements by dynamically and flexibly slicing the infrastructure and spectrum into virtual slices to achieve global optimized resource utilization.

4.1.2 Wireless network virtualization scheme

The virtualization process is summarized in Algorithm 1. We assume time in WNV to be slotted, and our study focuses on a single time period that comprises sufficient slots for the proposed mechanism to converge to the optimal solution.

Besides, users' location and requiring QoS traffic types was further assumed to be fixed within each time period.

As illustrated, in the initialization phase, the VSs are generated by the virtualization controller based on the current status of the network. Then at each scheduling period, the SDV controller executes the virtual resource allocation mechanism to realize the correspondence of demand and supply. Finally, SDV maps generated VSs to certain UEs through data plane.

It should be emphasized that realizing the aforementioned SDN-enabled architectures in the real world still requires a number of challenges to be overcome, including barriers of experimentation and data collection, etc.

4.2 Resource Sharing with Reverse Combinatorial Auction Theory

Reference Articles:

- [PI]: Energy Efficient Resource Allocation in Heterogeneous Software Defined Network: A Reverse Combinatorial Auction Approach.
- [PII]: Reverse Combinatorial Auction Based Resource Allocation in Heterogeneous Software Defined Network with Infrastructure Sharing.

In these two works, we investigate the problem of VRS at the infrastructure-level with different objectives. Corresponding to the business roles mentioned in SDV architecture, one MVNO, multiple InPs and the SDV controller are considered. To satisfy users' demand and reduce energy consumption, a reverse combinatorial auction mechanism is applied in which InPs bid for selling their infrastructure resources to an MVNO. The SDV controller with the resource allocation algorithm acts as a *resource broker*. The MVNO aggregates its subscribed users' demands and authorizes to the SDV controller to determine the winners. The process to match user and InP is formulated as winner determination problem (WDP).

In [PII], VRA problem in infrastructure sharing SDN architecture was formulated as a reverse combinatorial auction game, which enables different InPs to compete for offering the service to multiple UEs with diverse QoS requirements. System throughput was maximized. As the formulated problem is a nonconvex combinatorial game, we propose an iterative ascending price Vickrey (IA-PV) algorithm to solve it. The proposed scheme is strategy-proof and with low computing complexity. Specially, system throughput was enhanced significantly. As presented in Fig. 8, the enhancement was illustrated by presenting the convergence speed of the proposed iterative ascending price Vickrey (IA-PV) algorithm. For comparison, the pure allocation (PA) scheme is simulated as the benchmark, which iteratively selects the unallocated UE with minimum data rate requirements and assigns it to InPs regardless of the bidding price. As expected, it converges faster than the IA-PV algorithm, but cannot ensure higher system throughput during RA. Besides, the Hungarian scheme is also simulated for comparison, which is the exact algorithm with exhaustive optimal results for RA. To

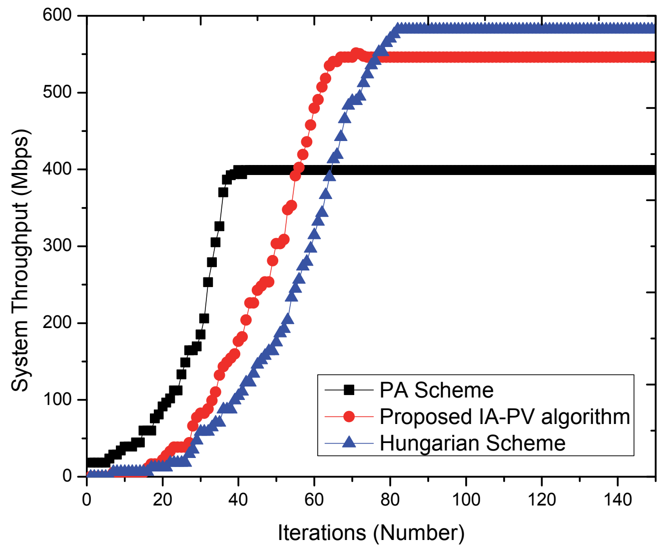

FIGURE 8 Comparision of system throughput and convergence speed with the PA scheme and hungarian scheme

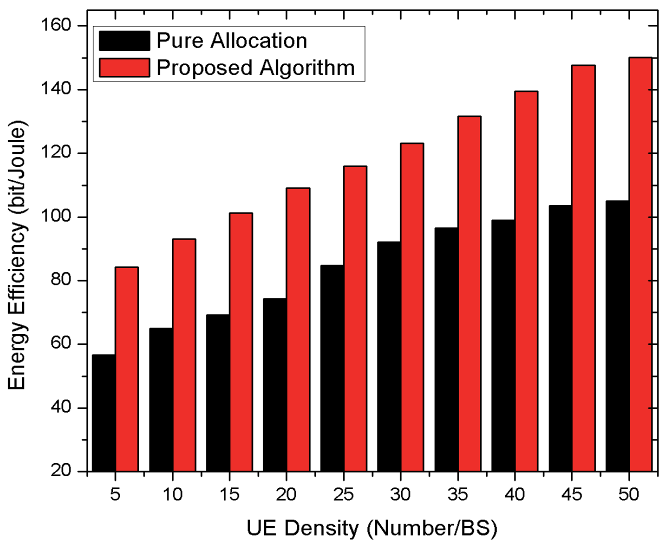

FIGURE 9 Comparison of energy efficiency between proposed IAPA algorithm and the PA, for UE density=50/BS, $P_{j,max} = 46\text{dBm}$ ($\forall j \in \mathcal{J}$)

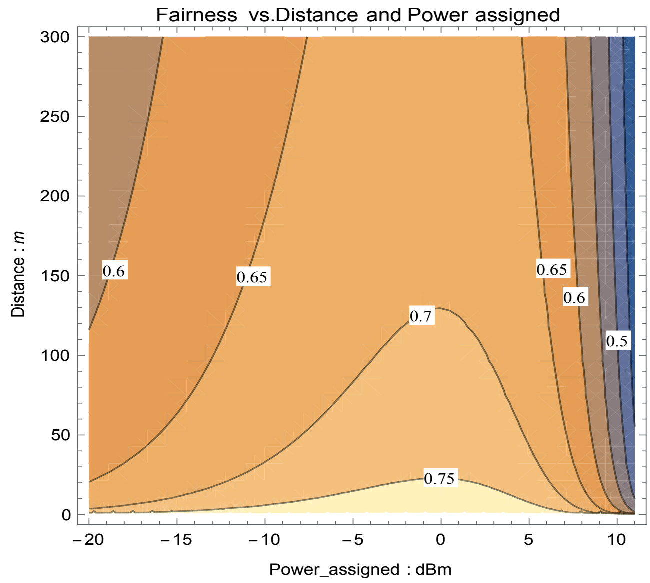

FIGURE 10 Fairness of R-CA game among multiple InPs

this end, we can see that, the convergence speed of IA-PV algorithm is much faster than Hungarian scheme, but only a little bit inferior system performance obtains finally.

In [PI], reverse combinatorial auction based resource allocation scheme was proposed by aiming at maximizing energy efficiency while taking different QoS constraints (maximum power requirement and user demand) into account. The formulated WDP problem in fractional form is non-convex with energy efficiency as objective and is hard to implement and solved within polynomial time. Similar algorithm named iterative ascending price auction (IAPA) algorithm was proposed to transform the fractional objective into subtractive form by exploiting the properties of fractional programming. The resulting IAPA algorithm is also demonstrated to be strategy-proof and with low computing complexity. In particular, the energy efficiency enhancement was illustrated in Fig. 9. From which, we can figure out that EE performance is strictly higher than PA scheme, it is because in our algorithm, bidders with higher valuation and bidding price would receive more attention from SDN controller according to.

Furthermore, fairness and utility were also analyzed. For example, we illustrate the *fairness* among different InPs with Fig. 10. It shows that, the *fairness* is not only depends on the relative distance d_{ji}, but also the power assigned by bidder j. For a certain power, expansion of distance leads to the decrement of fairness. While for certain distance d_{ji}, when power assigned is lower than 0 dBm, the fairness will be increased with power, but when power assigned is higher than 0 dBm, the throughput is increased not much with power, it is because when throughput improves obviously, the EE is increased accordingly, which leads to higher energy efficiency and so the higher fairness. We also illustrates the utility

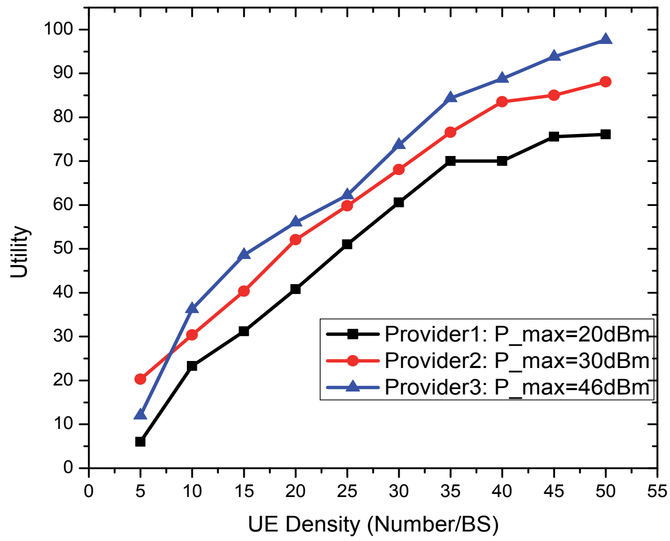

FIGURE 11 Utility of different network service providers vs. different UE density

among different InPs. Similarly, with Fig. 11, we can conclude that, higher maximum power constraint leads to higher utility, which in return proves the higher fairness controlled by SDV controller.

4.3 Multi-Flow Transmission with Double-Auction Theory

Reference Articles:

- [PIII]: A double auction mechanism for virtual resource allocation in SDN-based cellular network.
- [PIV]: Double Auction based Multi-flow Transmission in Software-defined and Virtualized Wireless Networks.

In these two works, we investigate the problem of VRS in flow-level (please refer to the classification in Section 2.1.2) with multi-flow transmission, which is proposed for improving user experience and balancing the traffic load, enables different cells to simultaneously schedule multiple data streams to the same user in their overlapping region by integrating heterogeneous RATs. The VS is considered and defined as *traffic flow* (TF), which is a new logical element and similar to the physical resource block in LTE systems. Generally speaking, TF in virtualization is a resource unit related to network services. To achieve synchronization, these TFs (isolated resource units) can be divided into packet blocks in the virtualization control plane, which is labeled with the virtual resources being carried

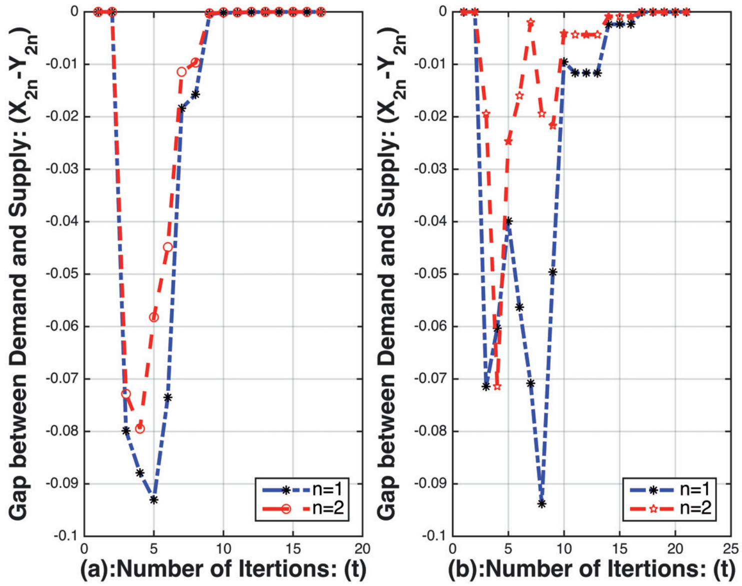

FIGURE 12 Demand and supply gap $(x_{ij} - y_{ij})$ evolution.

and the packet blocks sequence. Without knowing which virtual resources are allocated and how the virtual networks transmit, MVNOs reconstruct these packet blocks according to the sequence label and merge them into the original service flow to guarantee their end users' QoS requirements.

In [PIII], to address the heterogeneous nature of traffic demands, a double-sided auction mechanism was proposed by simultaneously considering diverse QoS requirements including the scheduling weight of users, different CapEx and OpEx of InPs, high-traffic load and low-traffic low scenarios, etc . Virtual resource allocation is formulated as a social welfare maximization problem. More energy efficient schemes were further considered in [PIV] by introducing the distance-related transaction cost and switching-off decisions. The hidden valuation function of bidders was elicited with a shadow price using an iterative auction process. The mechanism possessed the desirable economic properties in terms of truthfulness, individual rationality, budget balance and can finally achieve higher economic efficiency. Simulations are conducted with different configurations to show the effectiveness of the proposed scheme. By considering InPs and MVNOs simultaneously, as well as distance-related transaction cost, energy efficiency can be significantly improved. Moreover, this double-auction mechanism can also achieve obvious OpEx reduction by switching-off BSs during low-traffic-load period.

In Fig. 12, the effectiveness of a double-sided auction was illustrated by presenting he bidding gap $(X_{2n} - Y_{2n})$ between demand from MVNO2 (X_{2n}) and supply from InP to MVNO2 (Y_{2n}) iteration by iteration. We can notice that at

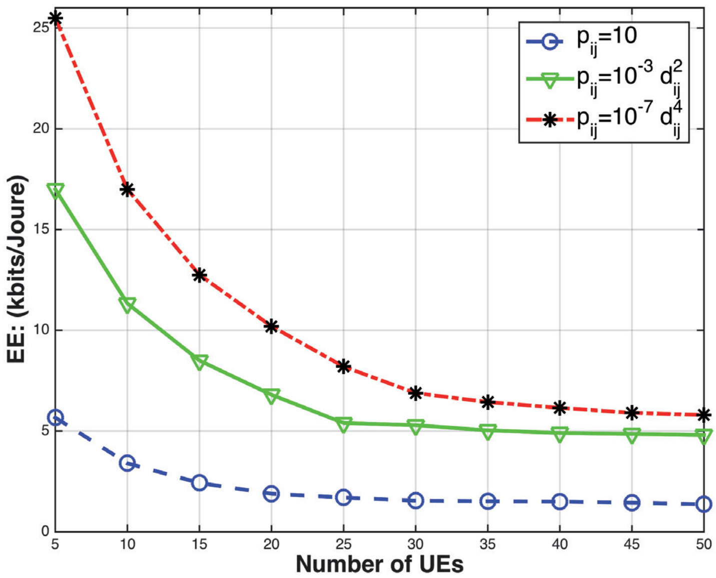

FIGURE 13 Energy efficiency (EE) with different numbers of UEs under devise definition of transaction cost.

equilibrium it holds $(X_{2n} - Y_{2n}) \rightarrow 0$. As shown, at the beginning, the bidding gap $(X_{2n} - Y_{2N})$ of both situation is nearly the same, especially before the 5^{th} iteration. After re-negotiating the transaction cost, ($p_{22} = 2 \rightarrow 10$, i.e. transaction cost between MVNO2 and InP2 is increased from 2 to 10), MVNO2, InP1 and InP2 change their bidding strategies accordingly, especially between the 5^{th} and 10^{th} iteration: as the price ($\Delta p_{22} = 10 - 2 = 8$) between MVNO2 and InP2 increased, to ensure the demanding QoS amount for its subscribed UE3, MVNO2 needs to increase its demand for InP1 X_{21} and significantly decrease the demand for InP2 X_{22}. This phenomenon demonstrates that at equilibrium, demand X_{mn} equals to supply Y_{mn}.

To ensure the heterogeneity and energy efficiency among different InPs and MVNOs, we introduce a *distance-related transaction cost*, which includes the costs associated with signaling, backhaul, etc. When MVNO $m \in \mathcal{M}$ purchases data from InP $n \in \mathcal{N}$, a transaction cost is incurred. Thus, even if two InPs provide the same speed of data rate, they may still be heterogeneous due to these transaction-related costs. Fig. 13 illustrates the relationship between EE and different definition of transaction cost p_{ij} with increasing UE number. Energy efficiency is defined as EE $= \frac{\sum_{i \in \mathcal{I}} y_{i1}}{\sum_{i \in \mathcal{I}} p_{i1}}$ with unit of (kbits/Joure) for reference. We take 3 different definitions of p_{ij} for showing their impact on EE. Compare the blue one ($p_{ij} = 10$) with the other two, we can clearly see that, without distance-related definition, EE is significantly lower, especially with the increasing number of UEs. Besides, in the distance-related p_{ij} scenarios (green and red lines), with higher pass loss ex-

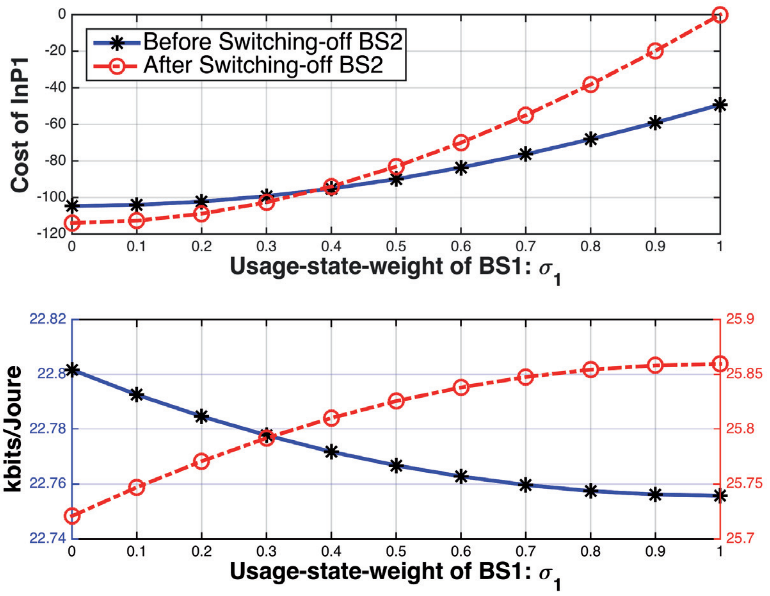

FIGURE 14 The cost and EE of InP1 with BS1 usage-stateweight changing before and after switching off BS2.

ponent parameter ($\alpha = 4$), EE performance (red line) obviously surpasses the one with lower $\alpha = 2$ (green line), even though, they all converge to stable EE with UE number increased. By which, we can conclude that, the definition of distance-related transaction cost p_{ij} can obviously improve the energy efficiency with the double auction mechanism during virtual-flow allocation period. Namely, the SDV controller can take charge of the energy-efficiency by adjusting parameter α.

Fig. 14 illustrates InP1's varying tendency of cost and energy efficiency with BS2's usage-state σ_1 when switching-off BS2. Parameter σ_j is defined as the indicator for distinguishing the usage state of BS and can also be used in the cost function for illustrating the InPs' behaviors concerning resource consumption.

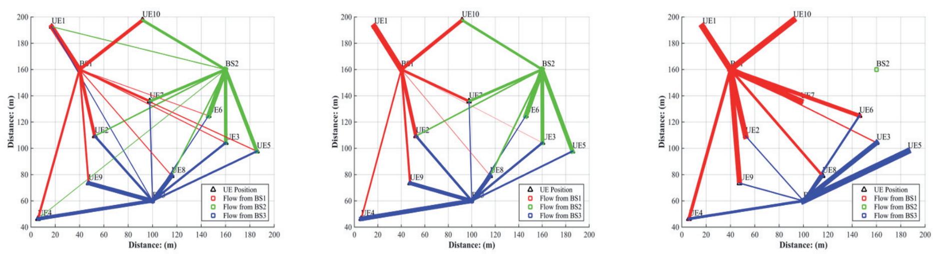

FIGURE 15 UE-BS association at the equilibrium with switching-off BS decision and different α.

This figure shows when it is better for InP1 to make the decision for switching-off BS2 for saving energy and improving self-utility. We can clearly see that, when BS1 is in light-usage-state ($\sigma_1 \leq 0.4$), switching-off BS2 won't decrease InP1's cost. This can happen only after BS1 becomes much busier (heavy-usage-state: $\sigma_1 > 0.4$), it is because OpEx can be averaged to be lower for InPs when served with more UEs (heavier-usage-state). Moreover, Fig. 14 (the lower part) shows that with our double auction mechanism, it is always better for InP1 to switch-off BS2 with light-usage-state weight, as this can lead to lower cost and higher EE simultaneously. UE-BS association at the equilibrium was illustrated in Fig. 15, where the thickness of the link indicating the amount of allocated flow (x_{ij}: from BS j to UE i). The first two subfigures illustrate how path loss exponent α affects virtual resource allocation. When α is small ($\alpha = 2$), nearly every UE needs all BSs for supporting their QoS requirements, while when α is larger ($\alpha = 4$), the UE-BS association changes significantly, where UEs can be satisfied through fewer BSs. Hence we can also infer that, when the interference level of the system is higher, the SDV controller can increase the value of α for reducing the inter- or intra-tier interference. However, a small part of the system utility will be sacrificed (e.g. $\mathcal{Z}(\mathbf{x}, \mathbf{y})$ decrease from 957.166 to 898.645). The last subfigure shows the UE-BS flow-association after switching-off BS2 (as $\sigma_2 = 0.1$). We can see that even though BS1 and BS2 share the task of transmitting flow to UE1-UE10 without BS3, system utility $\mathcal{Z}(\mathbf{x}, \mathbf{y})$ still has a slight increase (from 898.645 to 907.427). Hence we can conclude that, the SDV controller can control the system association and utility by changing the distance-related transaction cost p_{ij}.

4.4 Incentive Mechanism for Multiple InPs with Contract Theory

Reference Articles:

– [PV]: A Contract-based Resource Allocation Mechanism in Wireless Virtualized Network.
– [PVI]: Incentive Mechanism for Resource Allocation in Wireless Virtualized Networks with Multiple Infrastructure Providers.

In these works, novel contract theoretic incentive mechanisms were proposed to study how to provide quality-related services to multiple users in the WNVs. Particularly, the incentive mechanisms were studied and designed from the MVNO side, which is significantly different from our previous works and other related works. In the considered system, the MVNO needs to rent the physical network (radio resources) from the InP and operate it in a virtualized way to provide services to multiple user equipments (UEs). To the best of our knowledge, this concept is an early attempt to investigate the relationships between the MVNO and InPs and corresponding resource allocation problems from contract theory and network economic perspectives.

In our proposed mechanism, a WVN with multiple InPs and an MVNO was considered, where the interactions between the InPs and MVNO was modeled

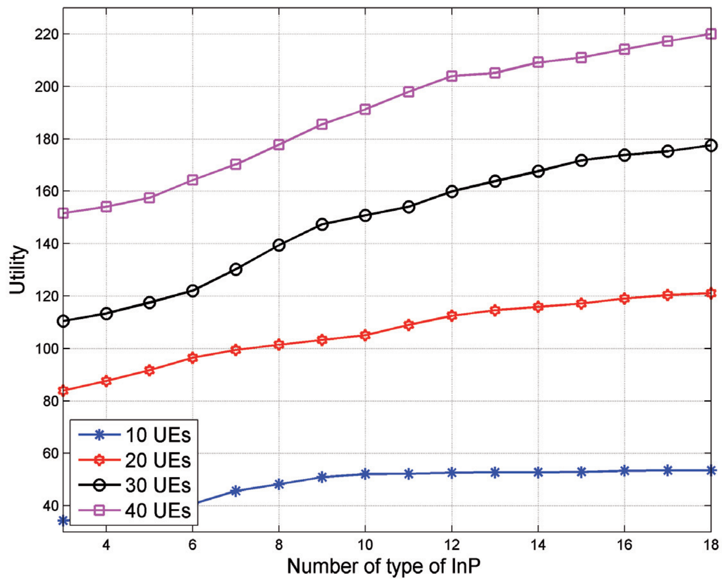

FIGURE 16 MVNO's utility with respect to number of UEs and InP types.

utilizing contract theory to provide qualified services to the UEs. With the objective to maximize the payoff of the MVNO, which is related to the service quality and utilized radio resources, we propose an incentive mechanism to motivate InPs to offer their radio resources to provide services. As the InPs are heterogeneous with a different preference toward joining in and providing services, in terms of operation cost, energy consumption, available spectrum, etc, a contract with incomplete (asymmetric) information was first analyzed in [PI], which is formulated as 0-1 mixed integer programming problem. Necessary definitions and lemmas were proposed and deduced to simplify the original problem to obtain the corresponding optimal contracts. More detailed analysis was presented in [PVI] concerning power allocation, a complete (symmetric) information scenario and more deduced theorems and lemmas.

With our proposed incentive mechanism, the more InP type (more InPs participat) classified, the more profit of MVNO can ensure. As illustrated in Fig. 16, when the WNV market becomes larger (more UEs and more InPs), MVNO can get more and better options to provide better services to the UEs. To evaluate the energy efficiency of our proposed mechanism, we introduced τ as the cost indicator of InP concerning transmit power in [PVI], where higher τ means higher willingness to join in the WNV market. The impact of the cost τ on the system performance was evaluated in Fig. 17. We can observe that InP's payoff in the case with complete information is larger than that in the case with linear pricing. When τ is small, the transmit power has less impact on the cost and the InPs may prefer to offer a higher transmit power to get more utility in the optimal

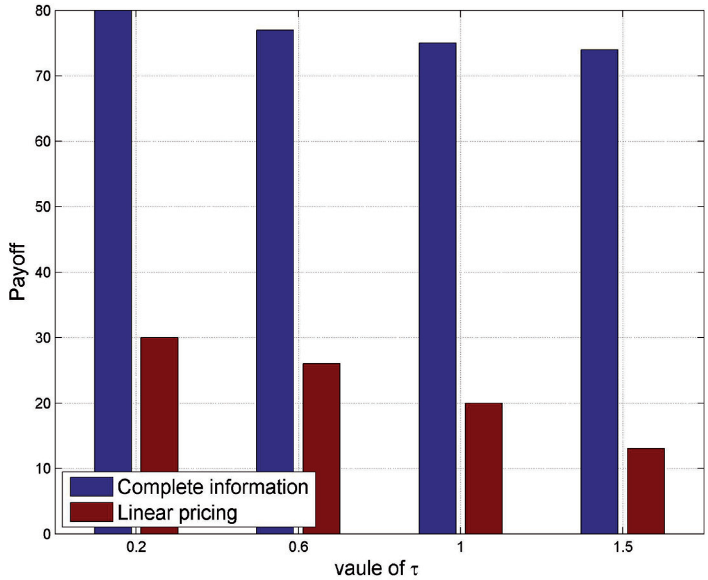

FIGURE 17 MVNO's utility with respect to value of cost parameter.

contract design. Therefore, the gap is not so big. When τ increases, this impact becomes larger, and InPs' transmit power may become smaller, which reflects on the service quality at the UE. In our scheme, however, as the transmit power is the optimization variable, the overall changes on the utility of the InP (cost of MVNO) will not be significant. However, for the case of linear pricing, the effect is more serious and thus, the gap becomes larger.

Therefore, the benefits of investigating contract-theoretic incentive mechanisms from MVNO's side included maximization of customer satisfaction and MVNO utility, greater flexibility and willingness of infrastructure sharing, accelerating the process of WNV market regulation, and etc.

4.5 Summary

In this chapter, we briefly introduced the research contributions and results related to the publications. System models and proposed schemes, as well as some achievements with figures were overviewed to make the included articles easier to understand.

5 CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

Focusing on reducing CapEx and OpEx of next generation wireless mobile network, this research discussed various novel resource allocation schemes in the context of SDN-enabled wireless network virtualization. In particular, different virtualization levels' slicing and sharing mechanisms with diverse QoS requirements and multiple business roles (InPs and MVNOs) were developed to obtain improvements in system throughput and energy efficiency with different business models.

By utilizing reverse combinatorial auction mechanisms, fairness, competitiveness and effectiveness when sharing infrastructure were ensured from InPs' perspective. Heterogeneous RATs, diverse users' demand and different capability of InPs were all included. The proposed mechanisms can be used not only as normal resource-management protocols at the infrastructure-level, but also to stimulate InPs to share their infrastructure when they have idle resources and want to earn more money.

By utilizing double-auction mechanisms, the interactions among multiple MVNOs and InPs were extensively analysed from different perspectives. The capability to achieve equilibrium, the conflicting interest expression of MVNOs and InPs, heterogeneous service quality requirements, and decisions about how to reduce energy consumption were all researched. The proposed mechanisms allowed multi-flow transmission, which corresponds to the development of 5G service-based architecture, i.e., user can simultaneously receive different service from different BSs, even different providers. Similarly, resource management protocols and profit gain can be achieved in flow/service-level as well compared with schemes at spectrum-level. MVNOs can take advantage of the proposed mechanisms to customize services to attract more users and increase competitiveness. The proposed mechanisms also design a profitable solution for owners of virtual SDN operators.

By utilizing contract theoretic mechanisms, InPs were encouraged as employees to join in the WNV market flexibly. The premise of entering this market is to agree the conditions offered by an MVNO (employer). The conditions were formulated and solved as optimal contracts that maximize MVNO's utility and quantify InPs' ability. The level of understanding InPs' capability depends on different MVNOs. More accurate information leads to more profit. Apart from acting as normal resource allocations mechanisms, the proposed incentive mechanisms can also be used to regulate the process of trading in the WNV market.

5.2 Limitations

Although this research involved careful investigation and preparation, I am still aware of its limitations and shortcomings.

First, the research was conducted with the assumption of the SDV operator is non-profit entity, who builds and runs the virtualized architecture without any income and balance. In fact, with the evolution of 5G, the SDV operator can be an InP, MVNO, or third-party with a specific price-charging mechanism. Even though [PIII] and [PIV] attempted to formulate the SDV operator's profit as the transaction cost, it is still far from the true charging behaviors of the SDV operator

Second, the proposed SDV architecture was a proof of concept due to the huge implementation effort and uncertainty on developing such a platform. Moreover, the involved multiple network operators and providers were assumed to tend to earn extra profit within the architecture of SDV. Even though the designed mechanisms were aiming at providing incentives to participated operators and providers, it may still be risky and not sufficiently attractive in the view's bigger operators, like Telia in Nordic, China Mobile in China, etc.

Third, since the simulation was designed to evaluate the performance of proposed algorithms, the scale of the simulation setting was small and only executed with Matlab, e.g., the simulated scenario was only executed within a specific area, the distribution of BSs were ideally located, the mobility of UEs were not considered.

In addition, as the proposed VRS mechanisms were designed to evaluate the behaviors of MVNOs and InPs concerning different demands and QoS requirements, the inherent effects of data transmitting were simplified, e.g., operating frequency of different operators were assumed to be different and the interference was assumed to be zero. In fact, it would influence the the QoE of users and the evaluation of benefits of both MVNOs and InPs.

5.3 Future Works

In this research, all the novel resource-sharing schemes were designed with SDN-enabled wireless virtualization architecture as prerequisite. Unfortunately, due to the rapid evolution of enabling technologies, the huge implementation efforts with open source platform, and the uncertain direction of 5G's development, the proposed SDV architecture for addressing flexibility and scalability was a proof of concept. Therefore, one of our main future works is to realize our SDV idea by implementing testbed.

The proposed schemes extensively analyzed the interactions among InPs and MVNOs. Additional research should be done regarding SPs in the future. By concerning SPs, content caching, mobile edge computing and other service-oriented issues will be involved in the WNV market, which will diversify the 5G ecosystem.

YHTEENVETO (FINNISH SUMMARY)

Virtual Resource Sharing -mekanismit ohjelmisto-ohjatussa ja virtualisoidussa langattomassa verkossa

Tulevaisuuden matkapuhelinverkoissa toimitaan tapahtumapohjaisella tiedonsiirrolla, jolloin ohjelmisto-ohjattujen verkkojen ja verkkotoiminteiden virtualisoinnilla päästään tarjoamaan tällainen ohjelmisto- ja palvelupohjainen verkkoarkkitehtuuri. Tämä tutkimus keskittyy minimoimaan operaattoreiden CAPEX- ja OPEX- kustannuksia erityisesti radioresurssien hallinnan näkökulmasta. Tähän liittyen tässä työssä esitetään ensiksi ohjelmisto-ohjattu ja virtualisoitu (SDV, software-defined and virtualized) arkkitehtuuri, jonka avulla verkon toimintoja voidaan virtualisoida eri tasoilla. Työssä kehitetty langattomien verkkojen virtualisointimenetelmä tarjoaa mahdollisuuden erottaa ja viipaloida langaton verkko ohjaus- ja tiedonsiirtotasoihin hyvin joustavalla tavalla. Tämän lisäksi työssä esitetään monitahoinen resurssien jakomekanismi (VRS, virtual resource sharing, se pohjautuu huutokauppa- ja sopimusteorioihin), joka takaa tasapuolisuuden ja kilpailun mobiilioperaattoreiden ja verkkopalveluiden tarjoajien kesken. Tämän VRS-mekanismin avulla voidaan taata erilaiset palvelunlaatuvaatimukset (esim. tiedonsiirtonopeus, viive, priorisointi), eri palvelutarjoajien väliset kilpailut sekä erilaiset järjestelmätason toiminnallisuudet (esim. järjestelmän läpimeno ja energiatehokkuus). Esitetyn VRS-mekanismin toimivuus on validoitu useilla erilaisilla matemaattisilla malleilla (huutokauppa-ja sopimuspohjainen resurssien jako). Eri menetelmien suorituskykyä on lisäksi erikseen arvioitu kattavilla järjestelmätason simulaatioilla.

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ORIGINAL PAPERS

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ENERGY EFFICIENT RESOURCE ALLOCATION IN HETEROGENEOUS SOFTWARE-DEFINED NETWORK: A REVERSE COMBINATORIAL AUCTION APPROACH

by

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Energy Efficient Resource Allocation in Heterogeneous Software Defined Network: A Reverse Combinatorial Auction Approach

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***Abstract*—In this paper, resource allocation for energy efficiency in heterogeneous Software Defined Network (SDN) with multiple network service providers (NSPs) is studied. The considered problem is modeled as a reverse combinatorial auction game, which takes different quality of service (QoS) requirements into account. The heterogeneous network selection associated with power allocation problem is optimized by maximizing the energy efficiency of data transmission. By exploiting the properties of fractional programming, the resulting non-convex Winner Determination Problem (WDP) is transformed into an equivalent subtractive convex optimization problem. The proposed reverse combinatorial auction game is proved to be strategy-proof with low computing complexity. Simulation results illustrate that with SDN controller, the proposed iterative ascending price algorithm converges in a small number of iterations and demonstrates the trade-off between energy efficiency and heterogeneous QoS requirement, especially ensures high fairness among different network service providers.**

I. Introduction

Future 5G network is expected to be heterogeneous in nature for providing gigabits data transmission for a large number of mobile devices [1]. Software Defined Network (SDN) is proposed as the future of 5G mobile networks by leveraging the programmability advantages in the separation of control-data plane [2]. Within this architecture, the network services provider (NSP) is no longer limited to the traditional operator that owns the infrastructure, but can also contain the virtual operators that are able to rent the infrastructure for providing services [3], [4]. There is no doubt that the radio access network will become much more heterogeneous, complex and denser, which calls for a new resource allocation mechanism to cope with the personal QoS requirement and system energy efficiency [5]. Meanwhile, widely deploying more and more access points to meet the increasing data demand inevitably increase the power consumption. Therefore, designing an energy efficient architecture to cope with the mixed usage of cells with diverse sizes and numbers of access points for a heterogeneous SDN access network is attracting more and more research attentions.

In this paper, we study how to efficiently coordinate the limited resource for different NSPs to maximize the profits and obtain higher fairness within SDN-based heterogeneous architecture. Most of the existing resource allocation schemes used in the traditional architectures are not appropriate for the heterogeneous SDN networks [6]–[8] due to the following reasons: 1) algorithm in the control plane lacks the availability of user equipment (UE) information (e.g., relative distance between the base stations and users), which requires extensive information exchange; 2) the lack of considering NSPs, as they are selfish and only focus on their own profit, which calls for a contiguous design of novel resource allocation scheme.

Motivated by the aforementioned observations, we study the SDN architecture with reverse combinatorial auction algorithm installed to address the energy efficient resource allocation problem by considering the competitive and fairness among multiple NSPs. Auction theory is introduced to provide an interdisciplinary technology for radio resource allocation (e.g., sub-carriers, time slots, and transmit power levels) in the wireless systems [9]. By using various auction approaches, such radio resources are efficiently allocated among users and providers in the cellular system [10]. The auction based method has been applied for the cognitive radio and mobile ad-hoc systems [11], [12] massively, but is less discussed in wireless cellular systems. In [12], the authors consider a two-stage resource allocation scheme with combinatorial auction in spectrum sharing problem, however, it does not consider more specific information about primary and secondary spectrum users. In [13], the authors propose one sequential single-item auction, where each user submits a bid based on the marginal increase in the data rate, but they did not consider multiple network providers.

In this work, the proposed reverse combinatorial auction based resource allocation scheme aims at maximizing energy efficiency while taking different QoS constraints (maximum power requirement and user demand) into account. The contributions of this work can be summarized as follows. First, we formulate the energy efficiency resource allocation problem among different NSPs as a reverse combinatorial auction game by considering different QoS requirement. The resulting non-convex WDP problem in fractional form is transformed into an equivalent subtractive optimization one by exploiting the properties of fractional programming. After that, this problem is solved by an iterative ascending price auction (IAPA) algorithm, which is proved to be strategy-proof. Simulation results illustrate that, with SDN controller, the proposed algorithm shows good results in terms of convergence speed and can offer high fairness allocation among NSPs. Moreover, it is also proved to be robust with QoS requirement changing.

II. System Model and Winner Determination Problem Formulation

A. System Model

We consider a heterogeneous SDN within one denser district, which consists of J Network Service Providers (NSPs) ($\mathcal{J} = \{1, ..., J\}$) and I user equipments (UEs) ($\mathcal{I} = \{1, ..., I\}$). The SDN controller acts as a central controller, which takes charge of all resource management related algorithms in this geographical area. Each NSP is assumed to operate on different licensed spectrum and is further assumed to observe only one base station (BS) with QoS requirement of maximum total power consumption constraint, $\mathcal{P}_{j,max} = [P_{1,max}, ..., P_{J,max}]$ separately (without loss of generality, we use NSP and BS interchangeably). UEs are assumed to be uniformly distributed in the geographical area with individual requirement of data rate $\mathcal{R}_{i,min}$. NSPs obtain heterogeneous resource of both channels and power constraints.

In this paper, we consider the problem of how to allocate the heterogeneous resource in order to achieve maximum energy efficiency (higher system throughput and lower system power consumption) and satisfy the QoS requirement. The energy efficient resource allocation (EE-RA) problem is formulated as a Reverse Combinatorial Auction (R-CA) Game. We introduce a non-profit central entity in this game, which is responsible for running the resource allocation auction game, called *resource broker*. The *resource broker* with algorithms for solving the auction game is installed on the SDN controller. The NSPs who observe resource (BSs) and money constraint ($\mathcal{P}_{j,max} = [P_{1,max}, ..., P_{J,max}]$) act as *bidders* and bid for the business with UEs. The UEs which want to join the network act as *sellers* or *items* with price requirement of ($\mathcal{R}_{i,min} = [R_{1,min}, ..., R_{I,min}]$).

B. Channel Efficiency

In this paper, the channel is modeled as the Rayleigh fading channel [8]. We define SNR_{ji} as the signal to noise ratio (SNR) from NSP $j \in \mathcal{J}$ to UE $i \in \mathcal{I}$,

$$\text{SNR}_{ji} = \frac{p_{ji}|H_{ji}^2|}{N_0}, \tag{1}$$

where p_{ji} is the allocated power from BS j to UE i, N_0 is the additive white Gaussian noise (AWGN) at the receivers with one-sided power spectral density. $|H_{ji}^2|$ is the channel gain, where $|H_{ji}^2| = d_{ji}^{-\alpha}|h_{ji}|^2$. $|h_{ji}|$ is the complex Gaussian channel coefficient which obeys the distribution $\mathcal{CN}(0, 1)$, d_{ji} is the relative distance from BS j to UE i, and α is the free space path-loss exponent.

We calculate the channel rate according to the SNR between BS j and UE i. r_{ji} is defined as the data rate received by UE i from BS j:

$$r_{ji} = \log_2(1 + \text{SNR}_{ji}) = \log_2(1 + \frac{p_{ji}|h_{ji}|^2}{d_{ji}^{\alpha} N_0}), \tag{2}$$

from which we can infer that, the channel rate r_{ji} is related to the transmission power p between transmitter j and receiver i, so we have $r(j, i, p) = r_{ji}$, and $\rho(j, i, p) = p_{ji}$, where ρ stands for that it is the function of p.

We define *Channel Efficiency* as the ratio between channel rate $r(j, i, p)$ and channel transmission power $\rho(j, i, p)$:

$$C_{ji}^{eff} \triangleq \frac{r_{ji}}{p_{ji}} = \frac{\log_2(1 + \frac{p_{ji}h_{ji}^2}{d_{ji}^{\alpha}N_0})}{p_{ji}},\ C^{eff}(j, i, p) = \frac{r(j, i, p)}{\rho(j, i, p)}, \tag{3}$$

where C_{ji}^{eff} is the calculation form of the *Channel Efficiency*, and $C^{eff}(j, i, p)$ means that *Channel Efficiency* is a function of power p.

C. Bidding Strategy of Reverse Combinatorial Auction

In this section, we define that, the bidding strategy composes two parts $(\mathcal{S}_j, \mathcal{B}_j)$ for every bidder. The first part is the bidding bundle, which is the subset $\mathcal{S}_j$ of the whole *items* $\mathcal{I}$. The second part is the associated bidding price $\mathcal{B}_j$, which will directly affect the final winner determination. The detailed bidding strategy is described as follows.

1) Bidding Bundle Expression: We define set $\mathcal{S}$ ($\mathcal{S} \subseteq \mathcal{I}$) as a bundle of variables representing the business connection between NSP and UE. It can range from $\emptyset$ to $\mathcal{I}$, so for every *bidder*, there are 2^I such bundles to be calculated and chosen.

2) Asymmetric Valuation of Bidding Bundle: In order to execute this resource auction game more realistically, we define the valuation of bundle $\mathcal{S}$ as $V_{j\mathcal{S}}$, which is also the ratio between channel rate and channel transmission power (see the definition in Section II-B), where $V_{j\mathcal{S}} \triangleq C_{j\mathcal{S}}^{eff} \triangleq \frac{\sum_{i\in\mathcal{S}} r_{ji}}{\sum_{i\in\mathcal{S}} p_{ji}}$, $\forall j \in \mathcal{J}$. This definition also expresses the asymmetric property of the valuation, which means when bidder j changes, the valuation of the same bundle $\mathcal{S}$ also changes. With the same definition method in (3), we have

$$V(j, \mathcal{S}, p) = \frac{r(j, \mathcal{S}, p)}{\rho(j, \mathcal{S}, p)} = \frac{\sum_{i\in\mathcal{S}} r(j, i, p)}{\sum_{i\in\mathcal{S}} \rho(j, i, p)},\ \forall j \in \mathcal{J}, \tag{4}$$

which means that the valuation of bundle $\mathcal{S}$ depends on not only the transmitter j, but also the allocated power ρ.

3) Bidding Price: To achieve incentive compatibility, the auction mechanism should be designed to guarantee that, the dominant bidding strategies of bidders are the truthful bidding strategies. So in this paper we consider Vickrey-Clarke-Groves auction [11]. VCG is a type of truthful auction, which means the bidder will bid the bundle according to its real valuation, no matter what other bidders' bidding strategy are:

$$B_{j\mathcal{S}} = V_{j\mathcal{S}},\ B(j, \mathcal{S}, p) = V(j, \mathcal{S}, p),\ \forall j \in \mathcal{J}. \tag{5}$$

Now the bidding strategy of bidder j would be pair $(\mathcal{S}_j, \mathcal{B}_j)$. Note that the whole bidding strategy space of bidder j is $\mathcal{C}_{\mathcal{S}}(\mathcal{I}) \times \mathbb{R}^+$, where $\mathcal{C}_{\mathcal{S}}(\mathcal{I})$ means the combination of choosing $\mathcal{S}$ from set $\mathcal{I}$.

4) Pay Price: The cost of bidder j should pay for *item* i is defined as *pay price* and expressed as $Q_{j\mathcal{S}}$ (also as $Q(j, \mathcal{S}, p)$). In order to extend the combinatorial resource auction to a strategy-proof auction mechanism, we define the *pay price* observing the properties of non-linearity and anonymity, where if $\exists\ \mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2$, then it does not mean $Q_{j\mathcal{S}} = Q_{j\mathcal{S}_1} + Q_{j\mathcal{S}_2}$ and if $\exists\ j \neq j'$, then it does not mean $Q_{j\mathcal{S}} = Q_{j'\mathcal{S}_1}$.

5) Bidder Utility: During the auction, each NSP obtains a gain by offering connection with a bundle of UEs. The difference between the valuation of bidding bundle and the *pay price* is what bidder j can obtain finally. We define the gain of bidder j as the utility, $U_{j\mathcal{S}}$:

$$U_{j\mathcal{S}} = \begin{cases} V_{j\mathcal{S}} - Q_{j\mathcal{S}}, & \text{if bidder j wins bundle } \mathcal{S} \\ 0, & \text{otherwise,} \end{cases} \tag{6}$$

where $U_{j\mathcal{S}}$ is the calculated payoff of bidder j for bundle $\mathcal{S}$. If bidder j wins, the utility will be calculated according to definition, and can be expressed as $U(j, \mathcal{S}, p)$ according to (4) and (5); if bidder j loses, SDN controller will charge nothing for the bidding.

D. Winner Determination Problem

The problem of identifying which set of bids to be accepted is usually been defined as the Winner Determination Problem (WDP). According to WDP, the objective is the *social welfare* maximization, which is the overall gain of both *bidders* and *sellers* (or *items*).

1) Bidding Language and Decision Variables: We refer to the non-exclusive bundle-bids as the bidding language, which is also can expressed as XOR language. Within this mode, each bidder can submit an arbitrary number of pairs $(\mathcal{S}_j, \mathcal{B}_j)$, however, at most one of these bids can win finally. We define $x_{j\mathcal{S}}$ as the decision variable, which means for certain bundle $\mathcal{S}$, whether bidder j wins or not:

$$x_{j\mathcal{S}} = \begin{cases} 1, & \text{if bidder j wins bundle } \mathcal{S} \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

$x_{j\mathcal{S}}$ expresses the relationship between bundle $\mathcal{S}$ and bidder j with decision space of $J \times 2^I$, which has the same meaning in section II-C1. With decision variable $x_{j\mathcal{S}}$, we rewrite many functions above as follows: bundle $\mathcal{S}$'s total rate can be rewritten as $r(x, p)$, total power consumption can be rewritten as $\rho(x, p)$. Therefore, the valuation in (4) can be rewritten as $V(x, p) = \frac{r(x,p)}{\rho(x,p)}$.

2) Social Welfare: We propose Theorem 1 for the definition of *social welfare*.

Theorem 1: The *social welfare* of this reverse combinatorial auction is the system *energy efficiency* γ, which is the proportion of system throughput $R(x, p)$ and system power consumption $P(x, p)$.

Proof: For bidder j, the welfare is the utility of bidding strategy $U(x, p)$, and for seller i, the welfare is the gain that bidder j has offered $Q(x, p)$. We define $A(\mathcal{X})$ as the sellers' total welfare and $B(\mathcal{X})$ as the bidders' total welfare:

$$\begin{aligned} A(\mathcal{X}) + B(\mathcal{X}) &= \sum_{x\in\mathcal{X}} \sum_{p\in\mathcal{P}} Q(x, p) + \sum_{x\in\mathcal{X}} \sum_{p\in P} U(x, p) \\ &= \sum_{x\in\mathcal{X}} \sum_{p\in\mathcal{P}} V(x, p), \end{aligned} \tag{8}$$

where $\sum_{x\in\mathcal{X}} \sum_{p\in\mathcal{P}} V(x, p) = \frac{\sum_{x\in\mathcal{X}} \sum_{p\in\mathcal{P}} r(x,p)}{\sum_{x\in\mathcal{X}} \sum_{p\in\mathcal{P}} \rho(x,p)} = \frac{R(x,p)}{P(x,p)} = \gamma$, the social welfare is the ratio between system throughput and power consumption. ■

3) Formulation of WDP: We formulate the WDP as a mixed 0-1 integer non-linear programming with the *social welfare* maximization and QoS requirement satisfaction.

$$\max_{x,p} \ \gamma = \frac{R(x, p)}{P(x, p)}, \tag{9}$$

$$\begin{aligned} \text{s.t.} \ & C1: x_{j\mathcal{S}} = \{0, 1\}, \ \rho(j, i, p) > 0, \ \forall \mathcal{S} \subseteq \mathcal{I}, \ \forall j \in \mathcal{J}, \\ & C2: \sum_{i\in\mathcal{I}} \rho(j, \mathcal{S}, p) \le P_{j,max}, \ \forall j \in \mathcal{J}, \\ & C3: \sum_{j\in\mathcal{J}} x_{j\mathcal{S}} \le 1, \forall i \in \mathcal{I}, \\ & C4: \sum_{j\in\mathcal{J}} r(j, i, p) \ge R_{i,min}, \ \forall i \in \mathcal{I}, \\ & C5: \sum_{\mathcal{S}\subseteq\mathcal{I}} x_{j\mathcal{S}} \le 1, \ \forall j \in \mathcal{J}. \end{aligned} \tag{10}$$

III. Iterative ascending price auction algorithm for energy efficient resource allocation

In this section, we propose an iterative algorithm for solving the problem in section II-D3. We first exploit the non-linear fractional WDP for converting the objective function into an equivalent subtractive one [14], upon which we successfully transform it into a convex combinatorial optimization problem.

A. Problem Transformation

Without loss of generality, we define the optimal maximum energy efficiency parameter as γ^*, and $\mathcal{F}$ as the set of feasible solutions of WDP problem in section II-D3:

$$\gamma^* = \frac{R(x^*, p^*)}{P(x^*, p^*)} = \max_{(x,p)\in\mathcal{F}} \frac{R(x, p)}{P(x, p)}. \tag{11}$$

Theorem 2: γ^* is achieved if and only if

$$\begin{aligned} & \max_{(x,p)} R(x, p) - \gamma^* P(x, p) \\ & = R(x^*, p^*) - \gamma^* P(x^*, p^*) = 0, \end{aligned} \tag{12}$$

where $\{x, p\}$ is any feasible solution of problem (9) to satisfy the constraints in (10).

Proof: The proof of Theorem 2 is presented in [14]. ■

B. Iterative ascending price auction algorithm for Energy Efficiency Maximization

In this section, we propose an iterative ascending price auction algorithm (IAPA algorithm) for solving the transformed convex combinatorial problem in (12). Based on the famous Dinkelbach method [14], we introduce one double loop mechanism. The outer loop is mainly dealing with the optimal γ, and the inner loop is the main iterative reverse combinatorial auction game. The SDN controller will take charge of the whole algorithm, both the outer loop and inner loop. Firstly, within the outer loop, SDN controller will control the energy efficiency parameter γ by changing the maximum iteration number K_{max} and convergence tolerance ε, the detailed is summarized in Algorithm 1. Secondly, within the inner loop, SDN controller will act as the *resource broker*

Algorithm 1 Outer Loop for EE parameter γ^*

Initialize the maximization number of iterations K_{max}, the maximum tolerance ε, maximum energy efficiency parameter $\gamma = 0$, iteration index $k = 0$ and BEGIN Outer loop:
repeat
  Solve the inner loop problem for a given γ and obtain resource allocation policies (x', p')
  if $R(x', p') - \gamma P(x', p') \leq \varepsilon$ **then**
    Convergence=**true**
    return $(x^*, p^*) = (x', p')$ and $\gamma^* = \frac{R(x', p')}{P(x', p')}$
  else
    Convergence=**false**
    Set $\gamma = \frac{R(x', p')}{P(x', p')}$ and $k = k + 1$
  end if
until Convergence=**true** or $k = K_{max}$

to control the whole reverse combinatorial auction game by determining an optimal allocation scheme which leads to a social optimality. In addition, the SDN controller will also calculate the payments and payoffs for *bidders*. The detailed is summarized in Algorithm 2.

As shown in Algorithm 1, in each outer loop iteration, we solve the following optimization problem for a given parameter γ:

$$\begin{aligned} \max_{(x,p)} \ \mathcal{Z}(x, p) \ &= R(x, p) - \gamma P(x, p), \\ \text{s.t. } &C1,\ C2, C3, C4, C5. \end{aligned} \tag{13}$$

While the introduced inner loop iterative reverse combinatorial auction game is one kind of combinatorial optimization problem with given γ, which is hard to be solved within polynomial time [10]. We propose an IAPA algorithm according to [15], which is proved to solve the reverse combinatorial auction game efficiently. In Algorithm 2, we introduce a strategy-proof price updating mechanism, where the price is updated by a greedy mode, and once the bidder submits a bid for items or bundle, the corresponding price named *hammer price* is fixed, otherwise the price is increased. This IAPA algorithm is also demonstrated to guarantee both individual rationality and incentive compatibility (*truthfulness*) in III-C.

SDN controller controls the whole reverse combinatorial auction by changing the price updating mechanism, we define $\mathcal{Q}$ as the updating mechanism:

$$\mathcal{Q} \leftarrow q = \frac{\min_{i \in \mathcal{I}} R_{i,min}}{\max_{j \in \mathcal{J}} P_{j,max}}, \tag{14}$$

where we can see, when the iteration t changes, $R_{i,min}$ and $P_{j,max}$ will accordingly increase and decrease. The price q_i changes in a non-monotonous way, which can also express the properties (non-linearity and anonymity) defined in section II-C4.

C. Strategy-proof

As the general definition, strategy-proof means reporting the true demand in each iteration auction is the best response for every bidder. We demonstrate the proposed IAPA algorithm ensuring the proposed bidding strategy in each iteration is the best response of every bidder j.

Algorithm 2 Inner Loop auction for RA (x^*, p^*)

Input Outer Loop given γ, **Initialize** BS total power assignment $P_j = 0$ and BS total throughput $R_j = 0$, iteration index $t = 0$, $\mathcal{J}$, $\mathcal{I}$, QoS vector $\mathcal{P}_{j,max}$ and $\mathcal{R}_{i,min}$
SDN controller Sets initial auction price q and update mechanism $\mathcal{Q}$ according to (14)
while $\mathcal{I}! = 0$ **do**
  Bidding Strategy Generation
  for all $j = 1...J$ **do**
    for all $i = 1...I$ **do**
      Calculate $p_{ji} = \frac{(2^{R_i} - 1) d_{ji} N_0}{|h_{ji}|^2}$ according to (2)
    end for
    Sort p_{ji} and $P_{j,max} \leftarrow \max(p_{ji})$
    while $P_j \leq P_{j,max}$ **do**
      $b_{ji} = R_i - q \times p_{ji}$
      if $b_{ji} > 0$ **then**
        Bidding Set $S_j \leftarrow i$ and Bidding price $B_j \leftarrow b_{ji}$
        $P_j = P_j + p_{ji}$
      end if
    end while
    Submit Bidding Strategy $\{S_j, B_j\}$ for every $j \in \mathcal{J}$
  end for
  SDN controller determines winner
  for all $i = 1...I$ **do**
    Sort b_{ji} with descending mechanism, and find index j' with $\max(b_{ji})$
    if $b_{j'i} \geq (R_i - \gamma p_{j'i})$ **then**
      $x_{j'i} = 1$, $x^* \leftarrow x_{j'i}$, $p^* \leftarrow p_{j'i}$, $P_j' = P_j' + p_{j'i}$
      $\mathcal{I} = \mathcal{I} - x^*$, $P_{j',max} = P_{j',max} - p_{j'i}$, $R_j' = R_j' + R_i$
    end if
  end for
  Set t=t+1, and Update $\mathcal{Q}$
end while

Theorem 3: The iterative ascending price resource allocation algorithm within inner loop is strategy-proof.

Proof: We consider two cases for bidding, where the strategy $(\mathcal{S}, \mathcal{B})$ of bidder j has true valuation $V(j, \mathcal{S}, p)$. 1) During the beginning round, the utility for bidder j is $V(j, \mathcal{S}, p) - q > 0$, if j quit this round and wait for another chance, it will lose the bundle which can maximize its final valuation; 2) During the following round, as the price q increases, the utility for bidder j will be $V(j, \mathcal{S}, p) - q < 0$, if j bids and finally wins this bundle $\mathcal{S}$, it will obviously get a negative surplus for the final energy efficiency valuation.

From the above analysis, we can conclude that the optimal bidding strategy for bidder j is to bid with its true valuation, otherwise, it will impair its own revenue and finally reduce the system energy efficiency, i.e., the proposed algorithm is strategy-proof. ∎

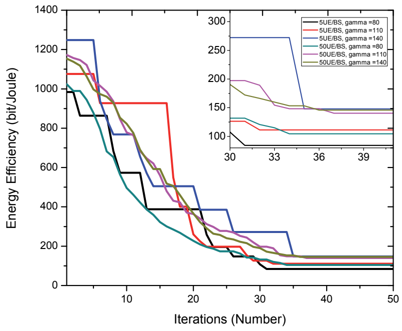

Fig. 1. Convergence speed of inner loop with different UE density and outer loop EE parameter γ setting, for $\mathcal{P}_{j,max}$ = 46dBm ($\forall j \in \mathcal{J}$)

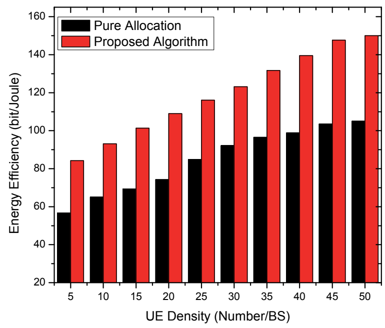

Fig. 2. Comparison of Energy efficiency between proposed IAPA algorithm and PA, for UE density=50/BS, $\mathcal{P}_{j,max}$ = 46dBm ($\forall j \in \mathcal{J}$)

D. Complexity

Traditional WDP in fact is NP-hard problem [10], especially with the non-convex objective and mixed integer decision variable. We demonstrate that the proposed iterative ascending price auction algorithm reduce the complexity of computational space significantly.

To obtain an optimal solution, an exhaustive search $(j, \mathcal{S}, p)$ is needed with complexity of $\mathcal{O}(J \times 2^{I+1})$ for the original problem (9). While in the proposed IAPA algorithm, the computing space during every iteration for submitting biding strategy is $\mathcal{O}(J(I^2+2I))$, where I^2 is the complexity of SDN controller executed bubble sorting algorithm. For deciding the round winner, the computing sorting mechanism's complexity is $\mathcal{O}(I(J^2+J))$. If the total number of inner loop is t, and outer loop maximization iteration is K_{max}, the computing space of the proposed algorithm is:

$$\begin{aligned}&\mathcal{O}((tK_{max})J(I^2+2I))+\mathcal{O}((tK_{max})I(J^2+J))\\&=\mathcal{O}((tK_{max})IJ(I+J+3))<\mathcal{O}(J\times 2^{I+1}),\end{aligned} \tag{15}$$

where we can conclude that the IAPA algorithm can reduce the complexity significantly compared to the original one (9).

IV. Performance Evaluation

In this section, we provide the simulation results to illustrate the performances of the proposed reverse IAPA algorithm. The considered SDN heterogeneous cellular network operates within one dense geographical area with radius of 0.5km with 3 NSPs. SDN controller will take charge of the whole radio resource management algorithms as well as signalling process. The UEs are randomly distributed within this area with mimimum data rate requirement ($\mathcal{R}_{i,min}$=10bit/s/Hz). We vary the UE density in the simulation from 5/BS to 50/BS. The considered path loss factor is α=4, AWGN is N_0 =-131dBm and h_{ji} obeys $\mathcal{CN}(0,1)$.

In Fig. 1, the convergence speed of the proposed IAPA algorithm with different UE density and different outer loop EE parameter γ setting is illustrated. Generally speaking, the proposed IAPA algorithm in inner loop converges fast, even for high UE density (50/BS) and high EE objective (γ=130) scenarios. Within the zooming-in figure in the upper-right-corner in Fig. 1, we can see that, the calculated EE objective γ^*=148 in the inner loop is better than the objective setting γ=130 of the outer loop. Besides, we can also conclude that, for certain γ, when UE density increases, the convergence speed is impaired a little bit, but the performance of EE will be improved. While for certain UE density, when EE objective setting γ increases, the performance will be heighten obviously.

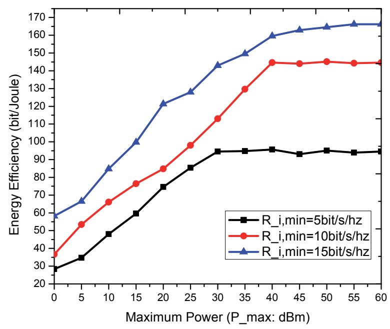

Fig. 3. Energy Efficiency versus maximum transmit power $\mathcal{P}_{j,max}$ ($\forall j \in \mathcal{J}$) and different $\mathcal{R}_{i,min}$ setting ($\forall i \in \mathcal{I}$), for UE density = 5/BS

In Fig. 2, we show the system energy efficiency performance of our proposed IAPA algorithm. For comparison purpose, the pure allocation (PA) is also simulated as the benchmark, which iteratively selects the unallocated UE with minimum data rate demand and assign it to NSPs regardless of bidding price. From which, we can figure out that EE performance is strictly higher than PA scheme, it is because in our algorithm, bidders with higher valuation and bidding price would receive more attention from SDN controller according to (4).

Fig. 3 illustrates the EE performance versus heterogeneous QoS requirement. It can be observed that when the maximum transmit power is large enough, e.g., $\mathcal{P}_{j,max} > 40$dBm, the energy efficiency approaches to a constant value, since the SDN controller is not willing to consume more power for serving the $\mathcal{R}_{i,min}$ QoS requirement. Besides, the speed for

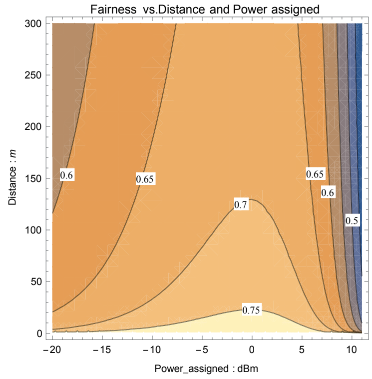

Fig. 4. Fairness of WDP between different network service providers, for $\mathcal{P}_{j,max} = 46$dBm ($\forall j \in \mathcal{J}$), for UE density = 5/BS

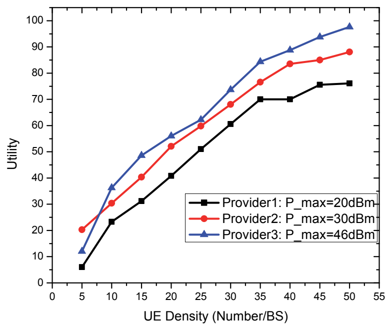

Fig. 5. Utility of different network service providers vs. different UE density

approaching stable EE is faster when $\mathcal{R}_{i,min}$ is smaller (case of $\mathcal{R}_{i,min} = 5$bit/s/Hz), but the energy efficiency performance is strictly higher when data rate requirement is higher (case of $\mathcal{R}_{i,min} = 15$bit/s/Hz). This is due to the fact that in the proposed algorithm, SDN controller tends to use the minimum power for satisfying minimum data rate requirement, so when $\mathcal{R}_{i,min}$ increases, the power allocated will be increased accordingly even though there is still retained power left.

In Fig. 4, we illustrate the *fairness* among different NSPs with a commonly used metric Jain fair index [10]. It shows that, the *fairness* is not only depends on the relative distance d_{ji}, but also the power assigned by bidder j. For a certain power, expansion of distance leads to the decrement of fairness. While for certain distance d_{ji}, when power assigned is lower than 0 dBm, the fairness will be increased with power, but when power assigned is higher than 0 dBm, the throughput is increased not much with power, it is because when throughput improves obviously (2), the EE (3) is increased accordingly, which leads to higher energy efficiency and so the higher fairness.

Fig. 5 illustrates the utility among different NSPs versus different UE density. Together with the observation in Fig. 4, we can conclude that, higher maximum power constraint leads to higher utility, which in return proves the higher fairness controlled by SDN controller.

V. Conclusions

In this paper, we introduce one architecture with SDN controller for energy efficient resource allocation among different NSPs by considering heterogeneous QoS requirements. In order to take the competitive and fairness into account, the heterogeneous EE-RA problem is formulated as a reverse combinatorial auction game. Since the fractional WDP is NP hard, we propose an IAPA algorithm with transforming fractional objective into subtractive form, which is also demonstrated to be strategy-proof and with low computing complexity. Simulation results illustrate that, with SDN controller, the proposed algorithm convergences fast and can offer high fairness allocation among NSPs. Moreover, it is also proved to be robust with QoS requirement changing. We are going to improve these results by implementing primal-dual auction algorithm, simulating it more realistically with software, e.g., NS-3, and further applying it with real SDN controller.

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PII

REVERSE COMBINATORIAL AUCTION-BASED RESOURCE ALLOCATION IN HETEROGENEOUS SOFTWARE-DEFINED NETWORK WITH INFRASTRUCTURE SHARING

by

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Reverse Combinatorial Auction based Resource Allocation in Heterogeneous Software Defined Network with Infrastructure Sharing

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***Abstract*—In this paper, resource allocation (RA) problem in heterogeneous Software Defined Network (SDN) with infrastructure sharing platform among multiple network service providers (NSPs) is studied. The considered problem is modeled as a reverse combinatorial auction (R-CA) game, which takes competitiveness and fairness of different NSPs into account. The heterogeneous RA associated with personal QoS requirement problem is optimized by maximizing the social welfare, which is demonstrated to be total *system throughput*. By exploiting the properties of iterative programming, the resulting non-convex Winner Determination Problem (WDP) is transformed into an equivalent convex optimization problem. The proposed R-CA game is strategy-proof and proved to be with low computational complexity. Simulation results illustrate that with SDN controller sharing environment, the proposed iterative ascending price Vickrey (IA-PV) algorithm converges fast and can obtain nearly optimal system throughput. It is also demonstrated to be robust and can ensure higher fairness and individual profit among different NSPs. With the fairness guaranteed, this infrastructure sharing SDN platform can attract more NSPs to participate, in order to achieve more profit and cost reduction.**

I. Introduction

Future 5G network is expected to be more heterogeneous and denser for providing gigabits data transmission for a large number of mobile devices [1]. Therefore, Network Service Providers (NSPs) seek to extend their infrastructure by installing more Base Stations (BSs) for increasing the capacity of their network [2]. While the additional infrastructure not only implies a rise in Capital Expenditures (CapEx), but also has a direct impact on higher Operational Expenditures (OpEx) [3]. Software Defined Network (SDN) is proposed as the future of 5G mobile networks by leveraging the programmability advantages in the separation of control-data plane [4]. Within this architecture, the coexistence of multiple NSPs in the same geographical area can lead to *infrastructure sharing* more easily. Besides, it can further enable NSPs to use their resources jointly for guaranteeing user service while achieving maximum system throughput and cost reduction [5]. There is no doubt that this infrastructure sharing SDN platform consequently calls for a new resource allocation mechanism to deal with different profit allocation among NSPs and also the personal QoS requirement.

In this paper, we study how to fairly considering the Resource Allocation (RA) problem among different NSPs, and meanwhile achieving the maximum system throughput within SDN-based infrastructure sharing architecture. Most of the existing resource allocation schemes used in the traditional architectures are not appropriate for the heterogeneous SDN networks due to the following reasons [6]–[8]: 1) algorithm in the control plane lacks the availability of user equipment (UE) information (e.g., relative distance between the base stations and users), which requires extensive information exchange; 2) the lack of considering NSPs, as they are selfish and only focus on their own profit, which calls for a contiguous design of novel RA scheme.

Combinatorial auction (CA) is a decentralized market mechanism and proposed as a good candidate to address the competitive behaviour of NSPs [9]. A RA algorithm based on auction method for uplink OFDMA system is proposed in [8] and proof to be an efficient way for ICIC management. In [10] and [11], the authors propose one combinatorial auction algorithm as an efficient resource allocation method for multi-user system and shown to be a suitable solution for mitigating the interference between adjacent cells. However, they all treat UEs as the *bidders* to bid for the channel resource and lacks of considering the combinatorial nature of solution space. While in [13], even though it considers the reverse auction game, it lacks of analysing heterogeneity and fairness among multiple NSPs, especially from the system throughput perspective.

In this paper, the proposed mechanism allows NSPs to reduce their financial costs significantly and encourage more NSPs to participate this platform. The contributions of this work can be summarized as follows:

- We formulate the RA problem in infrastructure sharing SDN architecture as a reverse combinatorial auction game, which enables different NSPs to compete for offering the service to multiple UEs with diverse QoS requirement.
- As the formulated problem is a nonconvex combinatorial game, we propose an iterative ascending price Vickrey (IA-PV) algorithm for solving it. The proposed scheme is proved to be strategy-proof and with low computing complexity.
- Simulation results illustrate that, with infrastructure sharing SDN platform, the algorithm can significantly reduce the energy consumption cost. Furthermore, it can also attract more NSPs to join this platform for saving OpEx and increasing profit.

II. System Model and Problem Formulation

A. System Model

We consider one geographical area with multiple NSPs. They operates in different frequency bands and have access to the infrastructure sharing SDN platform. A RA problem with multiple BSs and multiple UEs is studied, where multiple BSs are operated separately by different NSPs. We consider one NSP has only one BS in the considered area. The set of NSPs is donoted as $\mathcal{J} = \{1, \ldots, j, \ldots, J\}$), which are assumed to operate on different licensed spectrum (without loss of generality, we use NSP and BS interchangeably). There are I UEs ($\mathcal{I} = \{1, \ldots, i, \ldots, I\}$), which are assumed to be uniformly distributed and want to join the network with individual minimum data rate requirement $\mathcal{R}_{min} = [R_{1,min}, \ldots, R_{i,min}, \ldots, R_{I,min}]$.

For simplicity, we model the channel between BS and UE as the Rayleigh fading channel. SINR_{ji} is defined as the signal-to-interference-plus-noise ratio (SINR) from BS j to UE i:

$$\text{SINR}_{ji} = \frac{p_{ji}|h_{ji}|^2}{I_{int,i} + N_0}, \tag{1}$$

where p_{ji} is the transmit power from BS j to UE i. N_0 is the additive white Gaussian noise (AWGN) at the receivers with one-sided power spectral density (PSD). $|h_{ji}|^2$ is the channel gain, where $|h_{ji}|^2 = (d_{ji})^{-\alpha}h_0^2$. The h_0 is the complex Gaussian channel coefficient that obeys the distribution $\mathcal{CN}(0,1)$, d_{ji} is the relative distance from BS j to UE i, and α is the free space path-loss exponent. As the NSPs are all operated on different licensed spectrum and SDN controller can eliminate the interference from network layer, we hereby define $I_{int,i} = 0$.

Determined by Shannon capacity formula, we calculate the channel rate r_{ji} as:

$$r_{ji} = \log_2(1 + \text{SINR}_{ji}) = \log_2(1 + \frac{p_{ji}|h_0|^2}{d_{ji}^{\alpha}N_0}), \tag{2}$$

from which we can infer that, the channel rate r_{ji} depends not only on the power p_{ji}, but also the relative distance d_{ji}. In order to achieve maximum system throughput, we assume that every UE is pre-negotiated by NSPs and are able to access to all around BSs. However, how to balance the fairness between different BSs in order to achieve maximum system throughput as well as consume less power is the main studied problem in this paper.

B. Reverse Combinatorial Auction Game

We formulate this RA problem as a reverse combinatorial auction (R-CA) game in order to achieve high fairness among different NSPs. A non-profit entity called *SDN controller* with algorithms installed is introduced for running the heterogeneous resource allocation R-CA game. As it is a R-CA game, we consider spectrum resources occupied by NSPs as one of the *bidders* which submit bids for the bundle of UEs, in order to maximize the channel rate. The UEs which want to join the network will act as *sellers* or *items* with QoS requirement $\mathcal{R}_{min}$.

At the beginning of the auction, *SDN controller* will collect all the basic information, including the available number of NSPs J and UEs I. Then it will calculate the relative distance information d_{ji} and convey it to NSPs.

After receiving the basic information, NSPs will calculate the bidding strategies according to their valuation and submit them to *SDN controller*.

1) Bidding strategy: The bidding strategy of NSP $j \in \mathcal{J}$ composes of two parts: $(\mathcal{S}_j, B_j)$. The first part is the subset of UEs $\mathcal{S}_j \in \mathcal{I}$, which NSP j wants to offer the connection and resource for, called *bidding bundle*. The second part is the *bidding price*, which NSP j can offer for competing the link with UE i in subset $\mathcal{S}_j$.

Definition 1. *The subset of UEs $\mathcal{S}$ ($\mathcal{S} \subseteq \mathcal{I}$), which NSP $j \in \mathcal{J}$ wants to offer the network connection, to called* ***bidding bundle****. Bidding bundle $\mathcal{S}$ ranges from $\emptyset$ to $\mathcal{I}$.*

Before calculating the bidding price, it is necessary to define the valuation of bidding bundle, which can directly influence the final gains for every NSP. This paper considers a Vickery-Clarke-Groves (VCG) auction [14], a type of truthful auction with multiple items. In SDN controlled R-CA model, NSP will bid the the business with UEs according to their real valuation.

Definition 2. *We define the* ***valuation of bidding bundle*** *$\mathcal{S}$: $V(j\mathcal{S})$ as the total real data rate offered by NSP j,*

$$V(j\mathcal{S}) \triangleq \sum_{i \in \mathcal{S}} r_{ji}, \tag{3}$$

where r_{ji} is the data rate NSP j wants to offer for UE i.

Definition 3. *The price offered by NSP j for bidding bundle $\mathcal{S}$ is called* ***bidding price*** *$B(j\mathcal{S})$, which directly influences the final bidding results.*

As it is a VCG auction, we further have

$$B(j\mathcal{S}) \triangleq V(j\mathcal{S}) = \sum_{i \in \mathcal{S}} r_{ji}. \tag{4}$$

2) Utility of NSP and UE: SDN controller will take responsibility for the charging. In order to extend the combinatorial resource auction to a strategy proof auction mechanism by charging suitable price, we adopt the idea of LOS pricing scheme and consider linear anonymous prices [9].

Definition 4. *The price SDN controller charged of NSP j for bundle $\mathcal{S}$ is called* ***pay price*** *$Q(j\mathcal{S})$, which is the valuation of power consumption.*

σ_j is defined as the valuation of NSP j for its own power consumption.

$$Q(j\mathcal{S}) = \sigma_j p(j\mathcal{S}), \ \forall j \in \mathcal{J}. \tag{5}$$

where $p(j\mathcal{S}) = \sum_{i \in \mathcal{S}} p_{ji}, \ \forall j \in \mathcal{J}$, is the total power NSP j needs to pay for $\mathcal{S}$. p_{ji} is the power consumption from NSP j to UE i, according to (2), we have

$$p_{ji} = \frac{(2^{r_{ji}} - 1)d_{ji}^{\alpha}N_0}{|h_0|^2}, \tag{6}$$

where r_{ji} is the *bidding price* in Definition 3, offered by NSP j for UE $i \in \mathcal{S}$.

As the *SDN controller* is a non-profit entity, the utility of UE i is the net *pay price* $Q_{i\in\mathcal{S}}(j\mathcal{S})$ offered by NSP j. While the difference between the *bidding price* and *pay price* is what NSP j can obtain finally. So the net utility for every NSP j is:

$$U(j\mathcal{S}) = B(j\mathcal{S}) - Q(j\mathcal{S}) = \sum_{i\in\mathcal{S}} (r_{ji} - \sigma_j \frac{(2^{r_{ji}} - 1)d_{ji}^{\alpha} N_0}{|h_0|^2}). \tag{7}$$

Where we can see that, the utility $U(j\mathcal{S})$ depends not only on the distance d_{ji} between BS j and UE i, but also the data rate r_{ji} it wants to offer (bidding strategy) and the valuation of its power consumption σ_j.

C. Winner Determination Problem

After receiving the sealed bidding information $(\mathcal{S}_j, B_j)$ from NSPs and QoS requirement $\mathcal{R}_{min}$ from UEs, the *SDN controller* will determine the final bidding winners from system perspective. The problem of identifying which set of bids win has usually been defined as the Winner Determination Problem (WDP) [15]. We define $x(j\mathcal{S})$ as the decision variable of WDP, where

$$x(j\mathcal{S}) = \begin{cases} 1, & \text{if } \textit{NSP j's } \mathcal{S} \textit{ wins} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

According to the WDP, the objective is the social welfare maximization, which is defined as the overall gain of both NSPs and UEs [6].

Theorem 1. *The* ***social welfare*** *of this SDN controlled heterogeneous reverse combinatorial auction game is the system throughput.*

Proof: For UEs, the overall gain is the total utility of all subset $\mathcal{S} \subset \mathcal{I}$. For NSPs, the overall gain is the total utility of all $j \in \mathcal{J}$. According to the utility function in section II-B2,

$$\begin{aligned} &\sum_{\mathcal{S}\subset\mathcal{I}} Q(j\mathcal{S})x(j\mathcal{S}) + \sum_{j\in\mathcal{J}} U(j\mathcal{S})x(j\mathcal{S}) \\ &= \sum_{\mathcal{S}\subset\mathcal{I}} Q(j\mathcal{S})x(j\mathcal{S}) + \sum_{j\in\mathcal{J}} B(j\mathcal{S})x(j\mathcal{S}) - \sum_{j\in\mathcal{J}} Q(j\mathcal{S})x(j\mathcal{S}) \\ &= \sum_{j\in\mathcal{J}} B(j\mathcal{S})x(j\mathcal{S}), \end{aligned} \tag{9}$$

where the system welfare is the *bidding price* offered by NSPs, which is also the system throughput according to (3). ∎

The WDP for maximizing the system throughput with different QoS requirements is formulated as a 0-1 integer non-linear programming model.

$$\begin{aligned} &\max_{x(j\mathcal{S})} V(j\mathcal{S})x(j\mathcal{S}) = \sum_{i\in\mathcal{S}}\sum_{j\in\mathcal{J}} r_{ji}x(j\mathcal{S}), \\ \text{s.t. } &C1: \sum_{\mathcal{S}\in\mathcal{I}} x(j\mathcal{S}) \le 1,\ \forall j \in \mathcal{J}, \\ &C2: \sum_{j\in\mathcal{J}} x(j\mathcal{S}) \le 1,\ \forall i \in \mathcal{S} \subset \mathcal{I}, \\ &C3: x(j\mathcal{S}) = \{0,1\},\ \forall \mathcal{S} \subset \mathcal{I},\ \forall j \in \mathcal{J}. \end{aligned} \tag{10}$$

SDN controller will determine an optimal allocation scheme $x(j\mathcal{S})$ finally, which leads to maximum system throughput with WDP model.

III. IA-PV Algorithm for Heterogeneous Resource Allocation with Multiple NSPs

In this section, we propose a method named Iterative Ascending Price Vickrey (IA-PV) algorithm for solving the heterogeneous RA problem in (10), especially taking the fairness between different NSPs into account. The original WDP model is non-convex, NP-hard and combinatorial in nature, which is hard to be solved within polynomial-time. While the proposed IA-PV algorithm is one kind of approximation algorithm based on ascending VCG method [16], which is proved to be more efficient for solving the combinatorial auction game.

A. Description of IA-PV Algorithm

Because of the combinatorial nature, the design of many R-CA games is based on *ask price* [8]. The main difference among them are the *pricing scheme* and *price update mechanism*. In IA-PV algorithm, *SDN controller* controls the whole auction until achieve the social welfare. Firstly, *SDN controller* collects all the necessary information, calculates the *initial price* and announce it to all NSPs (bidders). Then NSPs calculates the possible *bidding strategies* $(\mathcal{S},B)$ according to their own utility function (7) and forward them privately to *SDN controller*. After that, *SDN controller* will determine the winner (named *round winner*) at this iteration based on the objective of maxing system throughput. Finally, *SDN controller* collects the *round winner* and updates the *ask price* for next iteration according to the *price update mechanism*.

1) Initial Price: we define the minimum UE data rate requirement as the basic reference for *initial price* q^0.

$$q^0 = \frac{\min_{i\in\mathcal{I}}(\mathcal{R}_{min})}{\eta}, \tag{11}$$

where η is the data rate valuation of NSPs by *SDN controller*, $\eta = \frac{\sum_{j\in\mathcal{J}}\sigma_j}{J}$. The use of η can significantly improve the algorithm convergence.

2) Bidding Strategies in iteration t: based on the *ask price* auction mechanism design, the bidding strategy of every NSP $(j \in \mathcal{J})$ has been transformed into whether accepts the current *ask price* or not. According to Definition 4, the *pay price* is the valuation of power consumption, we take the t=0 scenario as example and have

$$p_{ji}^0 = \frac{q^0}{\sigma_j},\ \forall j \in \mathcal{J}, \tag{12}$$

where p_{ji}^0 is the transmitted power NSP j can allocate for UE i at current *ask price*. Based on (2), we have the related *bidding price* b_{ji}^0:

$$b_{ji}^0 = \log_2(1 + \frac{p_{ji}^0 |h_0|^2}{d_{ji}^\alpha N_0}),\ \forall j \in \mathcal{J}. \quad (13)$$

We take advantage of KKT condition in NSP's utility function for deciding the *bidding bundle* of NSP. In iteration $t = 0$, the utility function can be transformed into

$$u_{ji}^0 = b_{ji}^0 - q^0 = \log_2(1 + \frac{p_{ji}^0 |h_0|^2}{d_{ji}^\alpha N_0}) - \sigma_j p_{ji}^0, \quad (14)$$

where the utility of NSP j is the function of power consumption $\mathbf{p} = p_{ji}^0$. We have KKT condition:

$$\begin{aligned} &\mathbf{u_{ji}(p)^0} = u_{ji}^0 > 0,\ \forall i \in \mathcal{S} \\ &\mathbf{du_{ji}(p)^0} = \frac{\partial \mathbf{u_{ji}(p)^0}}{\partial \mathbf{p}} > 0,\ \forall i \in \mathcal{S}. \end{aligned} \quad (15)$$

The *bidding strategy* of NSP j is: if it satisfies the KKT condition in (15) based on current *ask price* (q_i^0), it will be the element s_{ji}^0 of $\mathcal{S}$.

$$s_{ji}^0 = \begin{cases} 1, & \text{if } \mathbf{u_{ji}(p)^0} \geq 0, \mathbf{du_{ji}(p)^0} \geq 0, \\ 0, & \text{otherwise.} \end{cases} \quad (16)$$

So *bidding strategy* in current iteration is (s_{ji}^0, b_{ji}^0). We can see that, the calculating of (s_{ji}^0, b_{ji}^0) considers the power consumption and the competitiveness, which can further improve the *system efficiency* and fairness among NSPs.

3) Round Winner Determination Problem in iteration t: We define x_{ji}^t as the *round winner*,

$$x(j\mathcal{S}) = \begin{pmatrix} x_{j1}^0 & x_{j1}^1 & \ldots & x_{j1}^t & \cdots \\ x_{j2}^0 & x_{j2}^1 & \ldots & x_{j2}^t & \cdots \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{jI}^0 & x_{jI}^1 & \ldots & x_{jI}^t & \cdots \end{pmatrix}. \quad (17)$$

With x_{ji}^t, we successfully transformed WDP in (10) into a linear and convex form:

$$\begin{aligned} &\max_{x_{ji}^t} b_{ji}^t x_{ji}^t \\ \text{s.t. } &R1 : b_{ji}^t \geq R_{i,min},\ \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \forall t \geq 0, \\ &R2 : \sum_t \sum_{j \in \mathcal{J}} x_{ji}^t \leq 1,\ \forall i \in \mathcal{I}, \\ &R3 : x_{ji}^t = \{0, 1\},\ \forall i \in \mathcal{I}, \forall j \in \mathcal{J}. \end{aligned} \quad (18)$$

4) Price Updating mechanism: SDN controller controls IA-PV algorithm by changing the *price updating mechanism*, we define $\mathcal{Q}$ as the updating mechanism:

$$\mathcal{Q} \leftarrow q^t = q^{t-1} + \Delta,\ \forall t \geq 1, \quad (19)$$

where $\Delta > 0$ is the fixed increasing threshold. We can see that, when the iteration t changes, $\mathcal{Q}$ will accordingly update by a greed mode, that once a NSP submits a *bidding strategy*, the corresponding prices are fixed, otherwise the price are increased.

The *ask price* auction continues until all UEs' QoS requirements are satisfied (termination condition is $\mathcal{I} = \emptyset$). The detail of our IA-PV algorithm is described in Algorithm 1.

Algorithm 1 Iterative Ascending Price Vickrey Algorithm

Input channel parameters h_0, N_0, α; NSP valuation parameter σ_j and UE QoS requirement $\mathcal{R}_{min}$;
Initialize iteration index $t = 0$, initial price q^0 and updating mechanism $\mathcal{Q}$; calculates d_{ji}.
while $\mathcal{I}! = \emptyset$ **do**
  Bidding Strategy Generation
  for all $j = 1...J$ **do**
    for all $i = 1...I$ **do**
      1.Calculate transmission power p_{ji}^t in (12) and bidding price b_{ji}^t in (13) seperately;
      2.Calculate KKT $\mathbf{u_{ji}(p)^t}$ and $\mathbf{du_{ji}(p)^t}$ in (15).
      if $\mathbf{u_{ji}(p)^t} > 0$ & $\mathbf{du_{ji}(p)^t} \geq 0$ **then**
        Set $s_{ji}^t = 1$; $b_{ji}^t = b_{ji}^t s_{ji}^t$
      else if $\mathbf{u_{ji}(p)^t} > 0$ & $\mathbf{du_{ji}(p)^t} < 0$ **then**
        Set $s_{ji}^t = 1$; $b_{ji}^t \leftarrow \max_{\mathbf{p}} \mathbf{u_{ji}(p)^t}$.
      else
        Set $s_{ji}^t = 0$; $b_{ji}^t = 0$.
      end if
      Submiting Bidding Strategy (s_{ji}^t, b_{ji}^t).
    end for
  end for
  Winner Determination of SDN controller in (18)
  for all $i = 1...\mathcal{I}$ **do**
    Sort b_{ji}^t with decending mechanism
    Set $r_{i,max}^t = \max_{j \in \mathcal{J}} (b_{ji}^t)$
    if $r_{i,max}^t > R_{i,min}$ **then**
      Set $\mathbf{r_{i,real}} = r_{i,max}^t$, final data rate received by i.
      Set $x_{ji}^t = s_{ji}^t$, winner detemination in iteration t.
    end if
  end for
  Temination Condition
  if $x_{ji}^t = 1$ **then**
    Find element i and $\mathcal{I} = \mathcal{I} - i$.
  end if
  Price Updating Mechanism
  Update $q^t = q^t + \Delta$ according to (19).
  Set $t = t + 1$
end while
Output system throughput $\mathfrak{R} = \sum \mathbf{r_{i,real}}$, auction winner $x(j\mathcal{S})$ in (17) and total power consumption $\mathfrak{P} = \sum\sum\sum p_{ji}^t x_{ji}^t$.

B. Strategy-proof

Theorem 2. *The IA-PV algorithm is strategy-proof in each iteration for every NSP j.*

Proof: As general definition, strategy-proof means reporting the true demand in each iteration auction is the best response for every bidder [12].

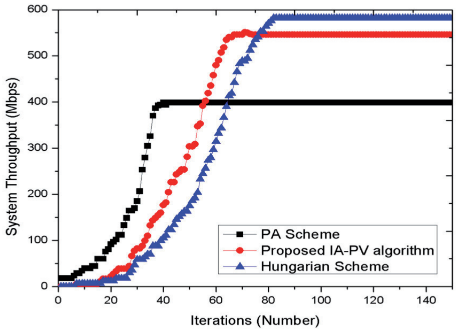

Fig. 1. Comparision of Convergence Speed with PA Scheme and Hungarian Scheme, for UE density = 30/BS

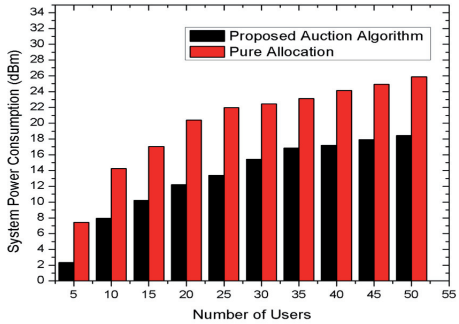

Fig. 2. Comparison of Power Consumption with PA Scheme

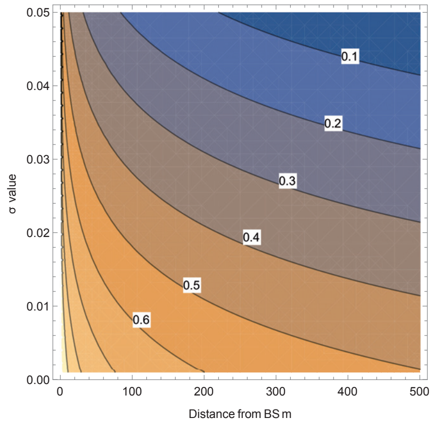

Fig. 3. Fairness of IA-PV algorithm for R-CA game among NSPs

From the algorithm description, we can conclude that the optimal bidding strategy for NSP j is to bid with its true valuation, otherwise, it will impair its own revenue and finally reduce the system throughput, i.e., the proposed algorithm is strategy-proof. ∎

C. Complexity

As mentioned above, the traditional WDP in nature is NP-hard problem, whose normal solution is the centralized exhaustive search. According to the number of UEs I and NSPs J, we have the complexity of the original problem, which can be denoted as $\mathcal{O}(J^I)$.

While in the proposed IA-PV algorithm, NSPs reveal their true valuation during each iteration t, the number of which is $(J * I)$, while the number of valuating the power allocation efficiency is also $(J * I)$. The total number for NSPs are $\mathcal{O}(2t(J * I))$. The complexity of *SDN controller* for executing bubble sorting algorithm is $\mathcal{O}(J^2)$, so the total complexity is $\mathcal{O}(t(2JI + J^2))$, which is much smaller than the original complexity:

$$\mathcal{O}(J^I) > \mathcal{O}(t(2JI + I^2)), \tag{20}$$

where we can conclude the IA-PV algorithm is significantly reduce the complexity compared with the original one.

IV. Performance Evaluation

In this section, we provide the simulation results to illustrate the performance of the proposed IA-PV algorithm. The considered SDN controlled heterogeneous cellular network operates within one dense geographical area with radius of 0.5km. There are 3 NSPs, whose channel bandwidth are assumed to be 1 Resource Block (=180kHz). The default *valuation of power consumption* for these 3 NSPs are σ_1=0.02, σ_2=0.03, σ_3=0.05. *SDN controller* takes charge of the whole signalling process, as well as the IA-PV algorithm for heterogeneous RA by considering fairness among NSPs. The UEs are randomly distributed within this area with mimimum data rate requirement ($\mathcal{R}_{min}$=[5,7]Mbps), and has density from 5/BS to 50/BS. The considered path loss factor is α=4, AWGN is N_0=-174dBm and h_0 obeys $\mathcal{CN}$(0,1).

In Fig. 1, the convergence speed of the proposed IA-PV algorithm is illustrated. For comparison purpose, the pure allocation (PA) scheme is simulated as the benchmark, which iteratively selects the unallocated UE with minimum data rate requirement and assign it to NSPs regardless of bidding price. As expected, it convergences faster than IA-PV algorithm, but cannot ensure higher system throughput during RA compared with IA-PV algorithm. Besides, the Hungarian scheme is also simulated for comparison, which is the exact algorithm with exhaustive optimal results for RA (the complexity is illustrated in III-C). From Fig. 1, we can see that, the convergence speed of IA-PV algorithm is much faster than Hungarian scheme, but only a little bit inferior system performance obtains finally.

In Fig. 2, we compare the system power consumption performance of our proposed IA-PV algorithm with PA scheme. We can figure out that a strictly lower system power consumption can be achieved by our IA-PV algorithm. It is because in our algorithm, NSPs with higher *bidding price* (also the proposed data rate b^t_{ji} offered by NSPs according to Algorithm 1) would receive much more attention according to (13) from *SDN controller*'s perspective, especially when determining the auction winners in (18). It is also important to evaluate the *fairness* of IA-PV algorithm among different NSPs. A commonly used measure of *fairness* is *Jain fair index*

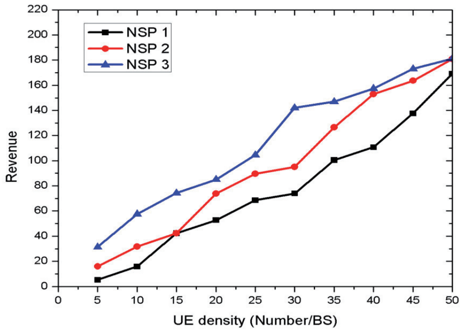

Fig. 4. Utility of different network service providers vs. different UE density

[17]:

$$\mathcal{F}(j,u) = \frac{\left(\sum_{i=1}^{J} u_j\right)^2}{J(\sum_{i=1}^{J} {u_j}^2)} \tag{21}$$

where $\mathcal{F}(j,u)$ ranges from 0 to 1, and indicates the degree of *fairness* of *SDN controller*. The larger of $\mathcal{F}(j,u)$ is, the higher *fairness* IA-PV algorithm has offered for different NSPs.

In Fig. 3, we can see that the *fairness* depends not only on the relative distance d_{ji}, but also the *valuation* of power consumption by different NSPs: σ_j. We take NSP $j = 1$ as reference. For a certain σ_j, the expansion of relative distance (d_{ji}) leads to the decrement of *fairness*. While for a certain relative distance (d_{ji}), the *fairness* will increase accordingly with the reduction of *valuation* σ_j. This conclusion is also consistent with the practical scenario, where the higher NSP values the power, the less UE it can offer at the same time, which in reverse obtain less opportunity during auction game.

Fig. 4 illustrates the utility among different NSPs versus different UE density. Together with the observation in Fig. 3, we can conclude that, lower *valuation* of power (σ_j) leads to higher utility, which in return proves the higher *fairness* controlled by *SDN controller*. Moreover, with the UE density increases, the revenue approaches to be stable, which can also be concluded from Fig. 3.

V. Conclusions

In this paper, we have investigated how to allocate the heterogeneous resource in infrastructure sharing geographical area in order to achieve higher system throughput, especially considering *fairness* among different NSPs. With *SDN controller*, we successfully formulate this RA problem as a R-CA game, whose *social welfare* is demonstrated to be the total *system throughput*. Since the resulting WDP is NP-hard, we propose an IA-PV algorithm by taking the competitiveness and fairness among NSPs in to account, which is also demonstrated to be strategy-proof and with low computing complexity. Simulation results illustrate that, with *SDN controller*, the proposed algorithm convergences fast and can obtain nearly optimal system throughput compared with Hungarian algorithm. Moreover, it can ensure higher fairness among NSPs and significantly reduce energy consumption from the system perspective, even with UE density changing. Finally, we can further conclude that, with infrastructure sharing SDN platform, it is possible to attract more NSPs, even Femtocell-holders to join in this platform in order to save OpEx, achieve higher system throughput, and further obtain more profits.

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PIII

A DOUBLE AUCTION MECHANISM FOR VIRTUAL RESOURCE ALLOCATION IN SDN-BASED CELLULAR NETWORK

by

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A Double Auction Mechanism for Virtual Resource Allocation in SDN-based Cellular Network

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***Abstract*—The explosively growing demands for mobile traffic service bring both challenges and opportunities to wireless networks, among which, wireless network virtualization is proposed as the main evolution towards 5G. In this paper, we first propose a Software Defined Network (SDN) based wireless virtualization architecture for enabling multi-flow transmission in order to save capital expenses (CapEx) and operation expenses (OpEx) significantly with multiple Infrastructures Providers (InPs) and multiple Mobile Virtual Network Operators (MVNOs). We formulate the virtual resource allocation problem with diverse QoS requirements as a social welfare maximization problem with transaction cost. Due to the high computational complexity of formulated problem and hidden information of InPs and MVNOs for SDN controller, we introduce the shadow price for ensuring the desirable economic properties as well as the total welfare of system. Simulations are conducted with different system configurations to show the effectiveness of the proposed SDN based wireless virtualization framework and double auction mechanism.**

I. Introduction

With tremendous growth of traffic and services in cellular networks, wireless virtualization has been proposed as one of the main evolution trends in the forthcoming fifth generation (5G) cellular networks [1]. The main idea of wireless virtualization is to decouple the infrastructure from the services it provides, therefore different services can share the same infrastructure, which can further improve resource usage efficiency, as well as reduce the CapEx and OpEx significantly [2]. Although wireless virtualization is a promising technology for next generation networks, many significant research challenges remain to be addressed before its widespread deployment in mobile wireless networks, especially how to design an architecture for encouraging multiple providers to share their infrastructure in order to save CapEx and OpEx [3].

Most existing work for wireless virtualization have taken advantages of game theoretic approaches on resource allocation. Specifically, the authors in [4], [5] and [6] have concentrated their works on applying power-pricing strategies for wireless virtualization, which solve the energy allocation and spectrum sharing problems separately. The cooperative game based spectrum sharing is analysed in [7] and a virtual resource allocation mechanism by using market equilibrium theory is proposed by [8]. The auction mechanisms for dynamic wireless resources (e.g., spectrum, transmission time) have been investigated in [9] and [10]. However, the authors above have only considered merely one Infrastructures Provider (InP) in the scenario, which lacks of flexibility for service selection. Besides, the network resources are auctioned without considering the heterogeneous services QoS requirements of User Equipments (UEs).

In this paper, we consider a general network scenario in which multiple InPs (legacy spectrum and infrastructure holders) and multiple MVNOs who provide services to their own subscribers coexist, especially for ensuring the fairness among InPs. InPs attempt to sell their own resources to MVNOs for monetary gains, while MVNOs try to acquire the resource usage permissions from InPs to satisfy own subscribers' communication goals, which generally introduces reward payoffs for InPs. In order to solve the above issues, we consider a double auction mechanism for allocating the physical resource owned by InPs to MVNOs to satisfy the special demands of their subscribers.

While a major confronted challenge is how to allocate the virtualized resource by both considering transmission delay requirement and priority of service offered by the InPs [3]. In order to realize heterogeneous virtualized resource allocation, we introduce SDN controller (SDN is one of the most promising technologies to realize virtual networks and SDN controller operates and manages virtual resource efficiently in response with a global view of network [11]) as the resource allocation control center, which can significantly reduce the signalling delay by decoupling the network to control and data plane. To jointly address the available resource and diversity demands for improving the end-to-end performance, the distinctive features of this paper are as follows:

- We propose a SDN-based wireless virtual resource allocation framework and a double auction mechanism for encouraging both the InPs and MVNOs for joining in order to save CapEx and OpEx significantly.
- The virtual resource allocation problem with diverse QoS requirements is formulated as a social welfare maximization problem with transaction cost.
- Iterative Double Auction (I-DA) algorithms with shadow price are proposed for solving the formulated high computational complexity problem, which ensures that truthful revelation is dominant strategy for both the InPs and MVNOs .
- Simulations are conducted to show the effectiveness of

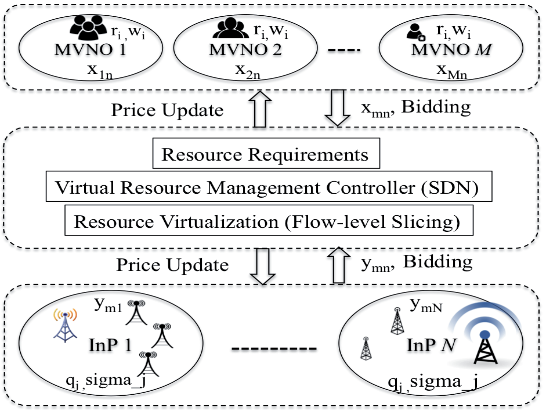

Fig. 1. SDN-based wireless network virtualization framework with multiple InPs and MVNOs

- the proposed scheme. It is shown that we can take the advantages of both wireless virtualization and double auction mechanism by considering InPs and MVNOs simultaneously to improve the resource usage efficiency.

II. System Model

In this section, we introduce the SDN-based virtual resource allocation framework and the double auction mechanism.

A. Wireless Network Virtualization

Wireless network virtualization can match resources by dynamically and flexibly slicing the infrastructure and resources into virtual networks to achieve global optimized resource utilization. Three logical roles can be identified after virtualization in Fig.1:

- **InPs**: they own physical substrate wireless networks, including radio resources (licensed spectrum), base stations (BSs), as well as the core networks and backhauls.
- **SDN controller**: it is in charge of dividing the service flow into multiple dedicated slices. The virtualized resource is based on *flow-level slicing* [3] and can enable multi-flow transmission.
- **MVNOs**: they lease the virtual resource dynamically form the InPs through SDN to satisfy their subscribers' communication requirements.

In this virtualized wireless framework, the MVNOs should pay the usage of physical resource dynamically. To lease physical resources to the MVNOs, the InPs charge fees based on MVNO's usage. MVNOs and InPs have pre-contracts about the price and charging rules.

B. Problem Formulation

Within one geographical area, we have a set of $\mathcal{N} \triangleq \{1, 2, \ldots, N\}$ InPs and a set of $\mathcal{M} \triangleq \{1, 2, \ldots, M\}$ MVNOs. Each InP $n \in \mathcal{N}$ has a set of $\mathcal{J}_n$ BSs. We denote $\mathcal{J} \triangleq \cup_{n\in\mathcal{N}}\mathcal{J}_n = \{1, 2, \ldots, J\}$ as the set of all BSs. Each MVNO $m \in \mathcal{M}$ has a set of $\mathcal{I}_m$ UEs, where $\mathcal{I} \triangleq \cup_{m\in\mathcal{M}}\mathcal{I}_m = \{1, 2, \ldots, I\}$ is denoted as the set of all UEs. The wide application of multi-mode terminals guarantees UEs simultaneous access to different RANs, which makes it suitable to access virtualized networks for multi-flow transmission.

The resource slice in this paper is defined as the set of virtual resources (e.g., traffic flows) requested by different MVNOs. We assume the resource slice is based on data rate [2]. By considering the UEs' QoS requirements, we define the UE's demand as the minimum data rate requirements ($r_{i,min}, \ \forall i \in \mathcal{I}_m$) with special time-dependency level. Consider the case that each MVNO m would like to require x_{ij} data rate for its UE i through BS j, we have $\sum_{j\in\mathcal{J}} x_{ij} \geq r_{i,min}$. We define the request vector for UE i to all J BSs as: $\mathbf{x}_i \triangleq (x_{ij} : \forall j \in \mathcal{J})$, and the total request data from MVNO m to InP n is $X_{mn} = \sum_{i\in\mathcal{I}_m}\sum_{j\in\mathcal{J}_n} x_{ij}$. The requests for all UEs of each MVNO are given by the matrix ($\mathbb{I}_m$ is the total number of UEs in MVNO m):

$$\mathbf{x}_m = (\mathbf{x}_i : \ \forall i \in \mathcal{I}_m), \ \mathbf{x}_m \in \mathcal{C}^{\mathbb{I}_m \times N}. \tag{1}$$

Meanwhile, each BS $j \in \mathcal{J}_n$ has total sliced data of $q_{j,max}$ at time t. InP $n \in \mathcal{N}$ want to allocate (sell) $y_{ji} \geq 0$ bytes of data through its BS $j \in \mathcal{J}_n$ to UE $i \in \mathcal{I}$, and $\sum_{i\in\mathcal{I}} y_{ij} \leq q_{j,max}$, so the selling vector for each InP n is $\mathbf{y}_j \triangleq (y_{ij} : \forall i \in \mathcal{I})$ and the total offered data from InP n to MVNO m is $Y_{mn} = \sum_{i\in\mathcal{I}_m}\sum_{j\in\mathcal{J}_n} y_{ij}$. The selling matrix for all InPs are given by matrix ($\mathbb{J}_N$ is the total number of BSs in InP n):

$$\mathbf{y}_n = (\mathbf{y}_j : \ \forall j \in \mathcal{J}_n), \ \mathbf{y}_n \in \mathcal{C}^{M \times \mathbb{J}_n}. \tag{2}$$

C. Utility functions

The concept of utility function is commonly used in microeconomics and refers to the satisfaction level of series actions allocated by decision maker [12] [13]. In this paper, we make use of utility function method for illustrating the business model of both InPs and MVNOs more practically.

For each MVNO $m \in \mathcal{M}$, the packets transmission delay of each flow should be kept low enough to guarantee the QoS requirements requested by its subscribers $i \in \mathcal{I}_m$, therefore utility depends on not only the total data rate MVNO offers, but also the time-dependency level. We define the utility function of MVNO $m \in \mathcal{M}$ as $\mathcal{F}_i^m(\omega_i, \mathbf{x}_i)$, where $\omega_i \in [0, 1]$ is the the weight of UE $i \in \mathcal{I}_m$ (dependency level of time). We define $\sum_{i\in\mathcal{I}_m} \omega_i = 1$. Assume that, the utility $\mathcal{F}_i^m(., \mathbf{x}_i)$ is an increasing, strictly concave and continuously differentiable function of $\mathbf{x}_i$ over the range $\mathbf{x}_i \geq 0$. The function $\mathcal{F}_i^m(\omega_i, x_i)$ has the characteristics as:

$$\frac{\partial \mathcal{F}_i^m(\omega_i, \mathbf{x}_i)}{\partial \mathbf{x}_i} > 0, \ \frac{\partial \mathcal{F}_i^m(\omega_i, \mathbf{x}_i)}{\partial \omega_i} > 0. \tag{3}$$

The definitions in (3) mean that when the required data rate $\mathbf{x}_i$ is the same, the UE $i \in \mathcal{I}_m$ who with the higher time-dependency weight ω_i can stimulate more profit for MVNO m; while when the weights ω_i are the same, the UE who needs higher data $\mathbf{x}_i$ can lead more profit for MVNO m. This utility function is more practical for measuring the business relationship between operators and subscribers. As the profit of MVNOs are additive, the aggregate utility of MVNO is:

$$\mathcal{F}_m(\mathbf{x}_m) = \sum_{i\in\mathcal{I}_m} \mathcal{F}_i^m(\omega_i, \mathbf{x}_i), \ \forall m \in \mathcal{M}. \tag{4}$$

For each InP $n \in \mathcal{N}$, the objective is to offer as much possibly accepted resource by the MVNOs as possible in order to gain more profit. In virtualized wireless system, we introduce busy level vector: $\sigma_j \in (0,1)$ for each BS, which can help balance the system flow allocation. It can be easily obtained under the supervisor of SDN controller. We define function $\Phi_j^n(\sigma_j, \mathbf{y}_j)$ as the utility of each InP $n \in \mathcal{N}$. From reality, we can assume that $\Phi_j^n(\cdot, \mathbf{y}_j)$ is an positive, increasing and concave function of vector $\mathbf{y}_j \geq 0$. So we have the characteristics of function Φ_j^n as:

$$\frac{\partial \Phi_j^n(\sigma_j, \mathbf{y}_j)}{\partial y_j} > 0, \ \frac{\partial \Phi_j^n(\sigma_j, \mathbf{y}_j)}{\partial \sigma_j} < 0. \tag{5}$$

The definitions in (5) mean when the allocated data rate is the same, access with higher busy level BS $j \in \mathcal{J}_n$ will occur higher cost, which in reverse decrease the profit for each InP n; while with the same busy level σ_j, the more data $\mathbf{y}_i$ BS $j \in \mathcal{J}_n$ can offer, the more profit InP n can obtain finally. As the utility is additive, for each InP n, the total welfare is:

$$\Phi_n(\mathbf{y}_n) = \sum_{j \in \mathcal{J}_n} \Phi_j^n(\sigma_j, \mathbf{y}_j), \ \forall n \in \mathcal{N}. \tag{6}$$

D. Social Welfare Maximization

SDN controller will act as broker and arrange the whole double-sided auction [4]. In order to ensure the heterogeneity between different InPs and MVNOs, we introduce transaction cost, which includes the costs associated with signalling, backhaul, etc. It is pre-negotiated and when MVNO $m \in \mathcal{M}$ purchases data from InP $n \in \mathcal{N}$, a transaction cost is incurred. Thus, even if two InPs provide the same amount data, they may still be heterogeneous due to these transaction-related costs. The transaction costs are assumed to be common knowledge.

In order to maintain fairness, SDN controller try to find the optimal $\mathbf{x}$ and $\mathbf{y}$ by solving the following social welfare maximization problem:

$$\begin{aligned} \max_{(\mathbf{x},\mathbf{y})} \sum_{m \in \mathcal{M}} \mathcal{F}_m(\mathbf{x}_m) \ &+ \sum_{n \in \mathcal{N}} \Phi_n(\mathbf{y}_n) \\ &- \sum_{m \in \mathcal{M}} \sum_{n \in \mathcal{N}} p_{mn} T_{mn}. \end{aligned} \tag{7}$$

$$s.t. \quad A1: \sum_{j \in \mathcal{J}} x_{ij} \geq r_{i,min}, \ \forall i \in \mathcal{I}, \tag{8}$$

$$A2: \sum_{i \in \mathcal{I}} y_{ij} \leq q_{j,max}, \ \forall j \in \mathcal{J}, \tag{9}$$

$$A3: y_{ij} \geq x_{ij}, \ \forall i \in \mathcal{I}, \ \forall j \in \mathcal{J}, \tag{10}$$

$$A4: y_{ij} \geq 0, \ x_{ij} \geq 0, \ \forall i \in \mathcal{I}, \ \forall j \in \mathcal{J}. \tag{11}$$

where $p_{mn} > 0$ is the pre-negotiated price between MVNO m and InP n, which is the cost per unit of data rate. If m and n has no contract, then $p_{mn} = \infty$. T_{mn} is total transmitted data amount between MVNO m and InP n, which depends on the final decision variable $\mathbf{x}$ and $\mathbf{y}$. It is obvious that at the equilibrium, $y_{ji} = x_{ij} holds, \ \forall i \in \mathcal{I}, \forall j \in \mathcal{J}$. So we define:

$$T_{mn} = \frac{X_{mn} + Y_{mn}}{2} = \frac{\sum_{i \in \mathcal{I}_m} \sum_{j \in \mathcal{J}_n} (x_{ij} + y_{ij})}{2}. \tag{12}$$

E. Problem Transformation with Shadow Price

Shadow price is a method for illustrating the marginal utility in constrained optimization in economics [14]. According to properties in (3) and (5), the problem in Section II-D is continuously differentiable, so we can firstly analyse it from its necessary and sufficient Karush-Kuhn-Tucker (KKT) conditions with *shadow price* $(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu})$:

$$\begin{aligned} \mathcal{L}(\mathbf{x}, \mathbf{y}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu}) = \ &\max_{(\mathbf{x},\mathbf{y})} \sum_{m \in \mathcal{M}} \mathcal{F}_m(\mathbf{x}_m) + \sum_{n \in \mathcal{N}} \Phi_n(\mathbf{y}_n) \\ &- \sum_{m \in \mathcal{M}} \sum_{n \in \mathcal{N}} p_{mn} T_{mn} \\ &- \sum_{i \in \mathcal{I}} \lambda_i (r_{i,min} - \sum_{j \in \mathcal{J}} x_{ij}) \\ &- \sum_{j \in \mathcal{J}} \mu_j (\sum_{i \in \mathcal{I}} y_{ij} - q_{j,max}) \\ &- \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} \nu_{ij} (x_{ij} - y_{ij}), \end{aligned} \tag{13}$$

where $\boldsymbol{\lambda} \triangleq (\lambda_i \geq 0 : \forall i \in \mathcal{I})$, $\boldsymbol{\mu} \triangleq (\mu_j \geq 0 : \forall j \in \mathcal{J})$ are the vector of Lagrangian multipliers corresponding to constraints (8) and (9) separately, and $\boldsymbol{\nu} \triangleq (\nu_{ij} \geq 0 : \forall i \in \mathcal{I}, \forall j \in \mathcal{J})$ is the matrix of Lagrangian multipliers for constraints (10).

The KKT conditions that yield to the optimal dual variables (shadow price) $\boldsymbol{\lambda^*}$, $\boldsymbol{\mu^*}$, $\boldsymbol{\nu^*}$ and optimal primal variables $\mathbf{x}^*$, $\mathbf{y}^*$ for problem (13) are given by the following set of equations:

$$\begin{aligned} &(B1): \frac{\partial \mathcal{F}_i^m(\omega_i, \mathbf{x}_i^*)}{\partial x_{ij}} = \frac{p_{mn}}{2} - \lambda_i^* + \nu_{ij}^*, \\ &(B2): \frac{\partial \Phi_j^n(\sigma_j, \mathbf{y}_j^*)}{\partial y_{ij}} = \frac{p_{mn}}{2} + \mu_j^* - \nu_{ij}^*, \\ &(B3): \sum_{j \in \mathcal{J}} x_{ij}^* = r_{i,min}, \\ &(B4): \sum_{i \in \mathcal{I}} y_{ij}^* = q_{j,max}, \\ &(B5): x_{ij}^* = y_{ij}^*, \end{aligned} \tag{14}$$

where $x_{ij}^*, y_{ij}^*, \lambda^*, \mu^*, \nu^* \geq 0$ are the global maximizers for the social welfare maximization problem (7).

III. Iterative Double Auction Algorithms

We can see that it is infeasible for the SDN controller to derive the optimal SWM solution through solving the problem above directly, due to the limited information of market, especially the valued weights of user priority for MVNO $\omega_i (i \in \mathcal{I}_m)$ and utility function for both MVNOs and InPs. Therefore, we take advantage of multi-stage design approach [14] for eliciting the hidden information and **Iterative Double Auction** (I-DA) algorithms are proposed by first analysing the bidding strategies both from MVNO and InP separately and then the optimal resource allocation problem is solved by SDN controller.

Algorithm 1 I-DA: Bidding Strategies for MVNOs

```
Obtaining current iteration shadow price: λ^(t), μ^(t), ν^(t)
for all m ∈ M do
    for all i ∈ I_m do
        Assign time-dependency weight ω_i for all UE i
        Calculate x_ij^(t) according to (A1):
            (B1): ∂F_i^m(ω_i, x_i^(t))/∂x_ij = p_mn/2 − λ_i^(t) + ν_ij^(t);
        if (B3): x_ij^(t) ≥ r_{i,min} then
            x_i^(t) ← x_ij^(t)
        end if
    end for
    x_m^(t) = (x_i^(t) : ∀i ∈ I_m)
end for
Uploading bidding strategies x_m^(t) to SDN controller
```

A. The Bidding Strategies

From the transformed problem in Section II-E, we can see that (B1), (B3), (B5) together combine the optimization bidding strategies for MVNOs, and (B2), (B4), (B5) together combine the optimization bidding strategies for InPs. We introduce the Vickery-Clarke-Groves (VCG) mechanism, which restricts that bidders must follow the truthful valuation for bidding [9]. After obtaining the current iteration shadow prices $\boldsymbol{\lambda}^{(t)}$, $\boldsymbol{\mu}^{(t)}$, $\boldsymbol{\nu}^{(t)}$ and assigned weights ω_i, σ_j of both UEs and BSs, MVNOs and InPs calculating their bidding strategies $\mathbf{x}_m$, $\mathbf{y}_n$ separately according to their true valuation of bidding utility: (4) and (6). As the optimal solution is satisfied by solving KKT conditions of primal problem, we solve the utility of both each MVNO m and InP n by (B1) and (B2), which are calculated by the pre-negotiated price p_{mn} between m and n and iteration shadow price $\boldsymbol{\lambda}^{(t)}$, $\boldsymbol{\mu}^{(t)}$, $\boldsymbol{\nu}^{(t)}$ produced by constraints (8) and (9). We can see the details in **Algorithm 1** and **Algorithm 2**.

B. Evaluating Dual Variables

We define the dual objective $g(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu})$ as an unconstrained maximization of Lagrangian (13):

$$g(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu}) = \max_{\mathbf{x},\mathbf{y}} \mathcal{L}(\mathbf{x}, \mathbf{y}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu}). \tag{15}$$

The dual optimization problem is:

$$\begin{aligned} &\min \; g(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu}), \\ &s.t. \; \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu} \geq 0. \end{aligned} \tag{16}$$

As the objective function in (13) is strictly concave and the constraint is compact and convex, the results guarantee that the primal problem (7) and dual problem (16) have the same solution, i.e. the duality gap between primal and dual function can be assumed negligible. Consequently, we can update the dual variables $(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu})$ by using a sub-gradient

Algorithm 2 I-DA: Bidding Strategies for InPs

```
Obtaining current iteration shadow price: λ^(t), μ^(t), ν^(t)
for all n ∈ N do
    for all j ∈ J_n do
        Assign busy-level weight σ_j for all BS j
        Calculate y_ij^(t) according to (B2):
            (B2): ∂Φ_j^n(σ_j, y_j^(t))/∂y_ij^(t) = p_mn/2 + μ_j^(t) − ν_ij^(t)
        for all i ∈ I do
            if (B4): Σ_{i∈I} y_ij^(t) ≤ q_{j,max} then
                y_j^(t) ← y_ij^(t)
            end if
        end for
    end for
    y_n^(t) = (y_j^(t) : ∀j ∈ J_n)
end for
Uploading bidding strategies y_n^(t) to SDN controller
```

Algorithm 3 I-DA: Resource Allocation by SDN controller

```
Initialize λ^(0), μ^(0), ν^(0)
Obtaining current bidding strategies from MVNO: x_m^(t)
Obtaining current bidding strategies from InP: y_n^(t)
if (B5): y_ij^(t) ≥ x_ij^(t) then
    if y_ij^(t) − x_ij^(t) ≤ ε then
        Checking Termination Condition
        if |F_m^(t) − F_m^(t−1)| ≤ ε_m and |Φ_n^(t) − Φ_n^(t−1)| ≤ ε_n
        then
            Set Convergence ← 1
        end if
    end if
end if
while (Convergence != 1) do
    Update sub-gradient for λ^(t+1), μ^(t+1) and ν^(t+1) by:
    λ_i^(t+1) = (λ_i^(t) + Δ · (r_{i,min} − Σ_{j∈J} x_ij^(t)))^+
    μ_j^(t+1) = (μ_j^(t) + Δ · (Σ_{i∈I} y_ij^(t) − q_{j,max}))^+
    ν_ij^(t+1) = (ν_ij^(t) + Δ · (x_ij^(t) − y_ij^(t)))^+
end while
```

descent method:

$$\begin{aligned} \lambda_i^{(t+1)} &= (\lambda_i^{(t)} - \Delta\lambda \frac{\partial \mathcal{L}(\cdot)}{\partial \lambda_i})^+, \; \forall i \in \mathcal{I}, \\ \mu_j^{(t+1)} &= (\mu_j^{(t)} - \Delta\mu \frac{\partial \mathcal{L}(\cdot)}{\partial \mu_j})^+, \; \forall j \in \mathcal{J}, \\ \nu_{ij}^{(t+1)} &= (\nu_{ij}^{(t)} - \Delta\nu \frac{\partial \mathcal{L}(\cdot)}{\partial \nu_{ij}})^+, \; \forall i \in \mathcal{I}, \forall j \in \mathcal{J}. \end{aligned} \tag{17}$$

where $()^+$ denotes the projection onto the non-negative orthant and ensures that feasibility constraints $\lambda_i^{(t+1)} \geq 0$, $\mu_j^{(t+1)} \geq 0$ and $\nu_{ij}^{(t+1)} \geq 0$. In order to simplify the overall parameter setting, we set here the $\Delta\lambda = \Delta\mu = \Delta\nu = \Delta$.

Meanwhile, we define $(\varepsilon_m, \varepsilon_n, \varepsilon)$ as the **convergence vector**. If the calculating bidding strategies satisfy the **convergence vector**, the I-DA algorithms terminate, otherwise, the

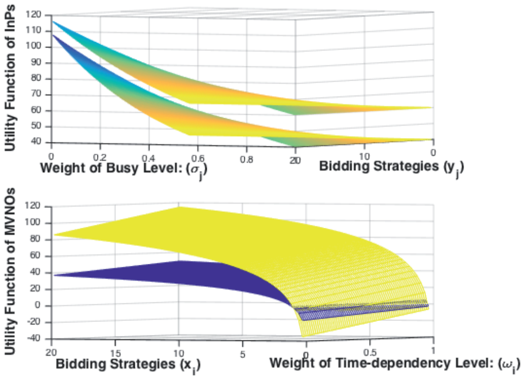

Fig. 2. The monotonicity of utility functions of InPs and MVNOs separately. Where $\beta_n = [20, 30]$ and $\alpha_m = [ln(2), (ln5)]$

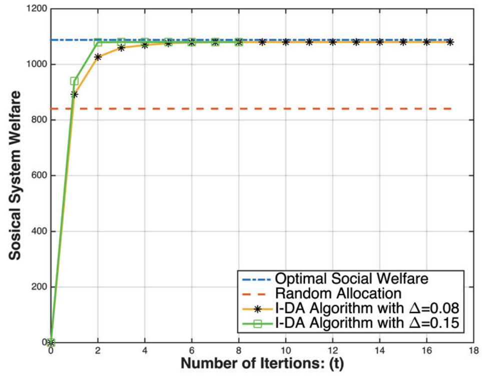

Fig. 3. The convergence process of I-DA and the effect of Δ

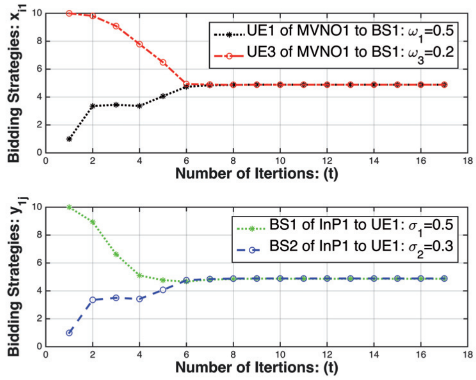

Fig. 4. The impact of UE's time-dependency ω_i and BS's busy-Level σ_j for bidding strategies x_{ij},y_{ij}

I-DA algorithms continue.

IV. Performance Evaluation

In this section, we provide the simulation results to illustrate theoretical analysis and performance of the proposed I-DA algorithm. We consider the scenario that there are two InPs and two MVNOs operate within the same geographical area. They are all controlled by one SDN controller and the system resources are sliced in the flow-level and can be specified as "data rate". The utility functions of both MVNOs and InPs are respectively defined as:

$$\mathcal{F}_m = 20 \cdot \sum_{i \in \mathcal{I}_m} \log_{\alpha_m}(e^{\omega_i} \cdot \mathbf{x}_i), \ m \in \{1, 2\} \tag{18}$$

$$\Phi_n = 2 \cdot \beta_n \sum_{j \in \mathcal{J}_n} e^{\frac{(1-\sigma_j)\cdot \mathbf{y}_j}{\beta_n}}, \ n \in \{1, 2\} \tag{19}$$

Through Fig. 2 we can see that, the setting is satisfied the monotonicity properties defined in (3) and (5). We suppose that there are 5 UEs that active with minimum data rate requirement $r_{i,min} = 10$(bit/s/Hz) during time-slot t. The first 3 belongs to MVNO1 and the last 2 belong to MVNO2. There are 3 BSs totally in the geographical area and at t, they all have maximum available data rate $q_{j,max} = 20$(bit/s/Hz). The first 2 belongs to InP1, and the last 1 belongs to InP2. MVNOs assign the UEs' weight ω_i according to their time-dependency level as $[0.5, 0.3, 0.2]$ and $[0.6, 0.4]$. Meanwhile, InPs assign the BS's weight σ_j according to their busy level as $[0.5, 0.3]$ and $[0.6]$. We assume the pre-negotiated transaction cost vector is $p_{mn} = [2, 3; 3, 2]$.

Fig. 3 shows the convergence of proposed I-DA algorithm and the effect of step size Δ in **Algorithm 3**. As shown in this figure, the gap between the I-DA algorithms and global optimal value is narrow, meanwhile it is absolutely larger than the random allocation value. This means the effectiveness of I-DA algorithms is equivalent to the optimal in terms of the overall utility. It can be found that the results with different Δ finally converge to almost the same utility value with only a small gap. However, the value of Δ affects the rate of convergence. $\Delta = 0.15$ gives higher convergence rate than $\Delta = 0.08$. Nevertheless, if we further increase the step, we will see that the I-DA algorithm does not converge to the optimal solution.

Fig. 4 illustrates the impact of QoS requirements ω_i and σ_j in the utility function for MVNO and InPs' bidding strategies iteration by iteration separately. For MVNOs, we take the bid evolution of UE1 and UE3 (belonged to MVNO1) to BS1 (belonged to InP1) as reference. As shown in this figure, MVNO1 changes the bidding strategies according to the time-dependency weight ω_i, the one with higher emergency service requirement (higher weight) has higher priority when bidding. The MVNO will increase the bids value for that UE accordingly and meanwhile decrease the bid value for UE who has less priority. We can see the same phenomenon for InPs, where BS2 with less busy level ($\sigma_2 = 0.3$) has higher priority than BS1 who has higher busy level ($\sigma_1 = 0.5$) when bidding. The reason is that, the InP can increase its own payoff by either increase the bidding value (y_{ij}) for less busy BS, or decrease the bidding value for higher occupied BS. The phenomenon also proves that MVNOs and InPs bid strictly and truthfully according to their utility function (defined in (3) and (5)) in I-DA algorithms.

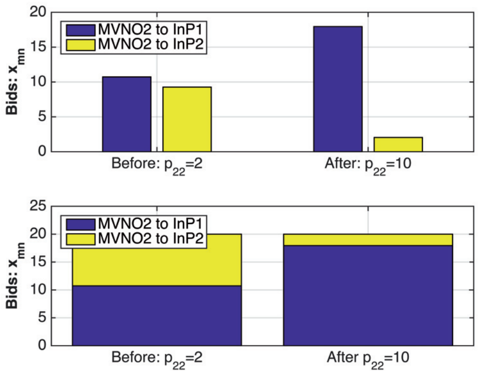

Fig. 5. Evolution of bidding with transaction cost p_{mn} increasing

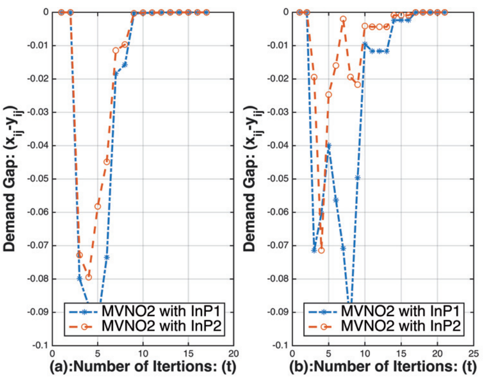

Fig. 6. Evolution of bidding gap with transaction cost p_{mn} increasing

In Figs. 5 and 6, we evaluate the effect of transaction cost p_{mn} on bidding strategies evolution. We take the bidding of MVNO2 to InP1 and InP2 as reference. As shown in Fig. 5, the transaction cost between MVNO2 and InP2 is increased from $p_{22} = 2$ per unit data rate to $p_{22} = 10$. Even though the final total bidding value are the same (according to UEs' demand), the bidding strategies to InP1 and InP 2 change significantly. MVNO2 evolves by decreasing bidding value from 8 (bit/s/Hz) to 2 (bit/s/Hz) to ensure higher utility. Besides, in Fig. 6, we can see that, at the beginning, the bidding strategies of MVNO2 are nearly the same, especially before 5-th iteration. While after re-negotiate the transaction cost, ($p_{22} = 2 \rightarrow 10$), the MVNO2, as well as InP1 and InP2 evolve the bidding strategies significantly, especially between 5th and 10th iteration. The reason behind the behaviour is that both MVNOs and InPs want to ensure the utility during bidding (see **Algorithm 1, Line 6** and **Algorithm 2, Line 6**).

Fig. 6 also presents the convergence of $\mathbf{x}_i$ and $\mathbf{y}_j$. Specially, we see that the gap between the requested demand and offered traffic gradually converges to zero, which satisfies the condition B5 in (14). This means that the MVNOs and InPs agree on the amount of data and negotiated transaction cost p_{mn}, as well as the SDN controller's central control.

V. Conclusions

In this paper, we investigated a SDN-based architecture for attracting multiple InPs and MVNOs sharing the virtual resource allocation in order to reduce CapEx and OpEx. We first virtualized the physical resources as virtual flow-level resources. After virtualization, MVNOs can help their own subscribers access to different InPs to get performance gain. Furthermore, we formulated the virtual resource allocation problem as an optimization problem by maximizing the total utility of system. In order to solve it efficiently, the virtual resource allocation problem is transformed to an iterative double auction problem with transaction cost. In this process, the MVNOs and InPs bid gradually according to their own utility function, as well as the shadow price introduced by SDN controller until the system converges. Simulation results also demonstrated the effectiveness and good convergence performance of our proposed I-DA algorithm. Future work in progress is to consider more realistic simulations with SDN, as well as the dynamic traffic requirement of UEs in the proposed SDN based virtualization architecture.

Acknowledgment

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DOUBLE AUCTION BASED MULTI-FLOW TRANSMISSION IN SOFTWARE-DEFINED AND VIRTUALIZED WIRELESS NETWORKS

by

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Double Auction based Multi-flow Transmission in Software-defined and Virtualized Wireless Networks

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***Abstract*—The explosively growing demands for mobile traffic services bring both challenges and opportunities to wireless networks. Wireless network virtualization is proposed as the main evolution path towards the forthcoming fifth generation (5G) cellular networks. In this paper, we propose a Software Defined and Virtualized (SDV) wireless network architecture for enabling multi-flow transmission with multiple Infrastructure Providers (InPs) and multiple Mobile Virtual Network Operators (MVNOs). In order to ensure the heterogeneity, we formulate the virtual resource allocation problem with diverse QoS requirements as a social welfare maximization problem with distance-related transaction cost. Due to hidden information of InPs and MVNOs for the auctioneer, we introduce a shadow price for ensuring desirable economic properties and total welfare for the system. Simulations are conducted with different system configurations to show the effectiveness and the energy efficiency performance of the proposed SDV wireless network framework and iterative double auction mechanism.**

***Index Terms*—SDN, wireless virtualization, multi-flow transmission, double auction, diverse QoS requirements, energy efficiency, switching-off BSs.**

I. Introduction

With the tremendous growth of traffic and services in cellular networks, there will be nearly seven trillion wireless devices around the world to be connected to serve the communication needs of seven billion people by 2020 [2]. Wireless virtualization has been seen as one of the main evolution trends in the forthcoming 5G cellular networks [3] [4] to provide users with a smooth service experience. The main idea of wireless virtualization is to decouple the infrastructure from the services it provides in order to allow different services to share the same infrastructure. This can further improve resource usage efficiency, as well as significantly reduce the capital expenses (CapEx) and operation expenses (OpEx) [5]. Meanwhile, another emerging technology, software defined networking (SDN) has been proposed as a novel approach to promote innovations in communication networks by leveraging the programmability advantages in the separation of control data plane [6], [7]. Though this innovation of network control and management, network service providers can offer on-demand end-to-end network provisioning services with guaranteed QoS more smoothly based on the specific requirements of subscribed UEs [8]. However, these two important areas have traditionally been addressed separately. Therefore, in this paper, we propose an innovative framework of Software-defined and Virtualized (SDV) wireless network for stimulating infrastructure sharing among different InPs and enabling diverse levels of QoS for different users.

Multi-flow transmission[1], which is proposed for improving user experience and balancing the traffic load, enables different cells to simultaneously schedule multiple data streams to the same user in their overlapping region by integrating heterogeneous RATs. However, little research effort on multi-flow transmission has been taken until now due to the competition and coordination among different InPs [10]–[12], especially about the virtual resource allocation. So in this paper, we take advantage of both multi-flow transmission and SDV for improving the end-to-end performance in next generation wireless network. By combining them, it is possible to make the utilization of wireless resources more efficient by flexibly adjusting the size of the flow slice, even significantly reducing the energy consumption and OpEx by switching-off BSs.

However, when SDV and multi-flow transmission are jointly considered, the problem of resource allocation becomes even more challenging, since much more fair allocation and coordination mechanisms are needed among multiple InPs, heterogeneous applications, and diverse user demands. Therefore, this paper proposes a double auction mechanism for addressing the problem of how to slice the physical resources (owned by InPs) energy-efficiently in order to satisfy the diverse QoS demands of MVNOs' subscribed UEs, as well as ensure the fairness among InPs. The main focuses are on the following perspectives:

- We propose a novel SDV wireless network architecture for implementing multi-flow transmission in order to stimulate different InPs sharing infrastructure, balance traffic flow, enable diverse QoS communication goals, and reduce both CapEx and OpEx significantly.
- To address the heterogeneous nature of traffic demand, we propose a double auction mechanism with transaction cost by simultaneously considering energy efficiency, cost expense and diverse QoS requirements. The virtual

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Part of this work was presented at IEEE PIMRC 2016, Valencia, Spain, Sept. 2016 [1].

[1]There are three types of implementation schemes for resource virtualization: spectrum-level slicing, network-level slicing and flow-level slicing. In this paper, we implement the flow-level slicing for balancing traffic flow [9].

resource allocation is formulated as a social welfare maximization problem.

- An iterative double auction (I-DA) algorithm is proposed to elicit the hidden valuation function of bidders with shadow price. Besides, the proposed I-DA algorithm is proved to be possessing the desirable economic properties in terms of *truthfulness*, *individual rationality*, *budget balance* and higher *economic efficiency*.
- Simulations are conducted with different configurations to show the effectiveness of the proposed scheme. By considering InPs and MVNOs simultaneously, as well as distance-related transaction cost, energy efficiency can be significantly improved. Moreover, it can also achieve obvious OpEx reduction by switching-off BSs during low-traffic-load period.

II. Related Work

Most existing work on virtual resource allocation has taken advantage of game-theoretic approaches. Specifically, the authors in [13] focus their works on applying power-pricing strategies for wireless virtualization to solve the energy allocation and spectrum sharing problems separately. Cooperative game-based spectrum sharing is analyzed in [14] and a virtual resource allocation mechanism using market equilibrium theory is proposed in [15]. Auctions for dynamic wireless resources (e.g., spectrum, transmission time) have been investigated in [16] and [17]. However, these authors above have considered only a single InP, where a provider lacks flexibility for service selection. Besides, the network resources were auctioned without considering the heterogeneous services requirements of users. Therefore, in our work, we studied the interaction of multiple MVNOs and InPs with heterogeneous QoS requirements, which is substantially more challenging and differs from other related economic mechanisms.

Double auction is proved to be a suitable mechanism for clearing markets with many buyers and sellers under incomplete information. In particular, a Walrasian auction scheme was proposed for mobile data offloading market, where mobile network operators lease third-party-owned Wi-Fi or femtocell access points to offload their mobile data traffic [18]. Authors in [19] designed a strategy-proof double auction mechanism with multi-tenant for bandwidth reservation. Both [20] and [21] studied the coalitional double auction mechanism for power allocation and spectrum reusability with multiple users separately. However, limited work has been done by designing strategy-proof and budget-balanced double auction mechanisms with transaction cost[2], which is crucial to be considered in a practical virtualized resource exchange market. The reason behind is when considering transaction cost, the problem becomes even more challenging, i.e. transaction cost lowers market efficiency, cuts down QoS quantity transacted, and reduces the speed of algorithm convergence [23]–[25]. Therefore in this paper, we adopt a different approach by designing a double auction market mechanism with transaction cost for ensuring the heterogeneous QoS requirements with multiple MVNOs and InPs. To our best knowledge, this paper is among the first to consider transaction costs into double auctions in virtual resource allocation market.

III. Software Defined and Virtualized Architecture

In this section, we first introduce the SDV architecture for enabling multi-flow transmission. Then the competition policy for resource sharing among InPs is discussed.

A. SDV Wireless Network Architecture

The SDV architecture is proposed for enabling multi-flow transmission with both wireless network virtualization and SDN. The considered user demands of MVNOs and supplying physical resources of InPs are geographically distributed. Therefore, the resource configuration among InPs can be further classified into local resource configuration and remote resource configuration [26]. As illustrated in Fig. 1, we only consider localized situation, which consists of two planes: the data plane and the control plane. The functions of each plane are described as follows:

- **Data Plane**: the data plane is responsible for the transmission of user traffic via virtual networks. Wireless resources, including the radio resource and infrastructure are sliced based on the instructions signalled by the Virtualization controller.
- **Control Plane**[3]: As different controllers can take charge of different functions and they can communicate through special interface among them [27], there are many SDV controllers in the designed control plane, we list three main controllers:
  a) ***Virtualization controller*** creates the virtual slice by dynamically and flexibly slicing the infrastructure and radio resources according to the decision made by the RA controller in order to achieve global optimized resource utilization. All virtual slices are independent and there is no interference or conflict between them.
  b) ***Info controller*** captures and updates the information of services requirements, network resources, and UEs. The state information is then transmitted to needed controllers, such as the RA controller, which can be helpful in properly allocating the infrastructure and radio resources.
  c) ***Resource Allocation (RA) controller*** runs the resource allocation algorithms. It captures the demands and supplies information from Info controller, and forwards the decisions to Virtualization controller.

Consequently, SDV can match resources with UEs' heterogeneous QoS requirements by dynamically and flexibly slicing the infrastructure and spectrum into virtual slices to achieve global optimized resource utilization.

[2]Transaction cost is defined as the cost associated with exchange of goods or services and incurred in overcoming market imperfections, which is a critical factor in deciding whether to make a product or buy it. It covers a wide range: communication charges, legal fees, informational cost of finding the price, quality, and durability, etc. [22]

[3]In this proposed SDV architecture, control plane is designed by taking the consideration of hierarchical virtualization control idea ("local"and "regional") [26]: SDV Regional Controller is a logically centralised entity that executes long-term optimisations and SDV Local Controller, which runs short-term optimisations.

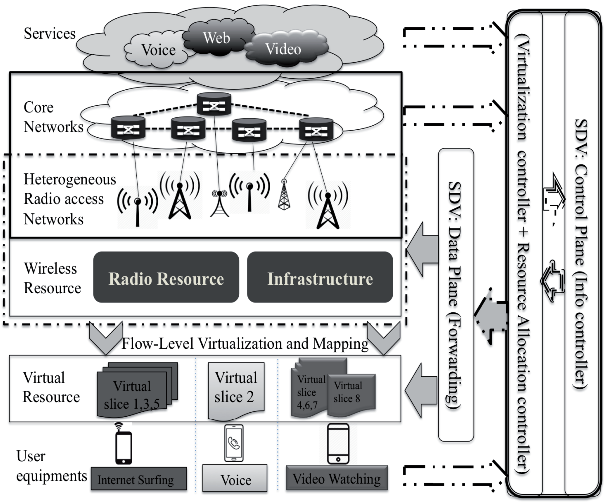


Fig. 1: The architecture of SDV wireless network for enabling multi-flow transmission.

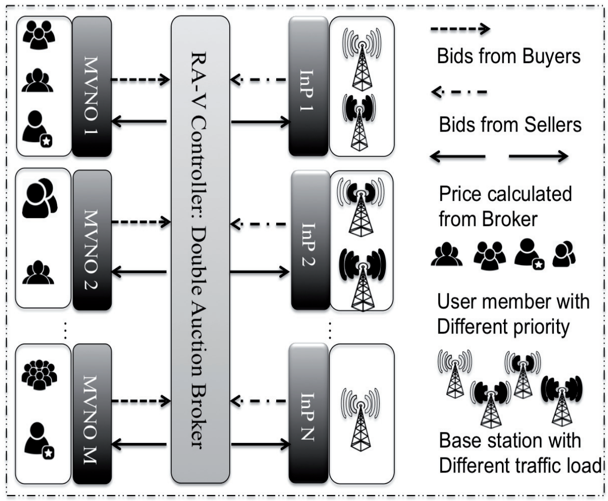


Fig. 2: Double auction mechanism for virtual resource allocation based on SDV architecture

B. Wireless network virtualization scheme

Firstly, by considering the essence of competition among multiple InPs, we formulate the resource allocation and sharing schemes among InPs in a double-sided-auction under the policy of competition. As shown in Fig. 2, three logical roles can be identified after virtualization with double auction mechanism: MVNOs, InPs and the Reource Allocation and Virtualization (RA-V) controller:

- MVNOs are *buyers*, who lease the virtualized network resources from InPs based on their subscribed UEs' demand. According to [11], UE here has a corresponding priority, which is consistent with the QoS level, i.e. the price paid to its operator MVNO.
- InPs are *sellers*, who own the physical wireless networks, including radio resources (licensed spectrum) and BSs[4], offer the connection with MVNOs based on the BSs' supply. According to [12], each BS has a corresponding traffic load indicator, which indicates its "usage-state".
- RA-V controller[5] is the *broker*, who is in charge of dividing and matching the wireless resource into multiple dedicated virtual resources and ensuring the equilibrium between demand and supply.

Secondly, the virtualized network resources are created by slicing the physical wireless resources (e.g., spectrum and/or infrastructure owned by InPs) into virtual pieces. In this paper, flow-level slicing is considered and defined as *traffic flow* (TF), which is a new logical element and similar to the physical resource block in LTE systems. Generally speaking, TF in virtualization is a resource unit related to network services. In order to achieve synchronization, these TFs (isolated resource units) can be divided into packet blocks in the virtualization control plane, which is labeled with the virtual resources being carried and packet blocks sequence. Without knowing which virtual resources are allocated and how the virtual networks transmit, MVNOs reconstruct these packet blocks according to the sequence label and merge them into the original service flow for guaranteeing their end users' QoS requirements.

[4]We define BS as the combination of RAN, core networks and backhaul.

[5]RA-V controller: the combination function of both resource allocation controller and virtualization controller introduced in Section III-A.

Finally, the virtualization process is summarized in Algorithm 1. We assume time to be slotted, and our study focuses on a single time period that comprises enough slots for the proposed mechanism to converge to the optimal solution. Besides, we further assume users' location and requiring QoS traffic types to be fixed within each time period. In the initialization phase, the TFs are generated by virtualization controller based on the current status of the network. Then at each scheduling period, RA-V controller executes double auction mechanism to realize the correspondence of demand and supply. At last, SDV maps generated TFs to certain UEs through data plane.

IV. Double Auction Mechanism Design

The system model with double auction design target, different utility and cost function of InPs and MVNOs, as well as distance-related transaction cost are discussed first. Then the problem is formulated as a social welfare maximization problem.

A. Auction Design Target

A more realistic scenario of a market with transaction cost for ensuring QoS heterogeneity is considered, where the buyers and sellers only know their own utility functions and the broker (here the RA-V controller) is not aware of the actual demands and supplies of MVNOs and InPs. Hence, we aim to achieve the following properties for the double auction based multi-flow transmission mechanism, where the following first three properties are necessary conditions for a practical and useful double auction design [28] and the remaining one quantify the effectiveness of the designed auction mechanism:

1) *Individual rationality*: Bidders' expected utility from participation is no less than his or her utility from nonparticipation.

Algorithm 1 Virtualization in the proposed SDV architecture

1: **Initialization:**

a) *Information Collection*: Info controller collects background network status, potential participating InPs, MVNOs and their corresponding QoS requirements including minimum demands and maximum supplies.

b) *TF definition*: Virtualization controller defines TF properties (e.g., time length, data rate, and priority) for each virtual flow, based on the pre-agreements with InPs.

c) *Slicing*: Virtualization controller generates certain number of virtual TFs for InPs.

2: **Scheduling:**

a) *Resource allocation*: The *RA-V controller* allocates an appropriate number of virtual TFs to each MVNO based on their QoS requirements (e.g., delay and data rate).

b) *Matching*: InPs transmit physical resources (e.g., BS, radio resource) to each MVNO through data plane according to RA-V controller's allocation results. MVNOs convert the properties of each TFs to data rate requirements and prepares the physical resources for each user.

3: **Pricing:** SDV controller charges suitable prices from the final winning buyers and sellers.

2) *Truthfulness*: Bidders cannot benefit from bidding differently from their true valuation.
3) *Budget-balance*: The auctioneer's expected payoff (total payments from the buyers, less than the revenues of the sellers and the needed transaction costs) is non-negative.
4) *Economic efficiency*: The total social welfare (the sum of the values of all bidders) should be the best possible. However, since reference [29] shows that it is impossible to simultaneously achieve truthfulness, budget-balance, and maximum efficiency simultaneously, we focus on an auction design that satisfies the above three properties, while making best efforts to improve the *auction efficiency*[6].

Besides, this double auction mechanism should also enable the coexistence of multiple InPs in the same geographical area, stimulates infrastructure sharing, guarantees the QoS requirements of user service and can even reduce energy consumption by switching-off BSs with light traffic load.

B. The System Model

Within one geographical area, we have a set of $\mathcal{N} \triangleq \{1, 2, \ldots, N\}$ InPs and a set of $\mathcal{M} \triangleq \{1, 2, \ldots, M\}$ MVNOs. Each InP $n \in \mathcal{N}$ owns a set of $\mathcal{J}_n$ BSs. We denote $\mathcal{J} \triangleq \cup_{n\in\mathcal{N}}\mathcal{J}_n = \{1, 2, \ldots, J\}$ as the set of all BSs. Similarly, each MVNO $m \in \mathcal{M}$ has a set of subscribed $\mathcal{I}_m$ UEs, where $\mathcal{I} \triangleq \cup_{m\in\mathcal{M}}\mathcal{I}_m = \{1, 2, \ldots, I\}$ is denoted as the set of all UEs. Key notations are summeraized in Table I. For simplification, we define UEs' demand as the minimum data-rate requirements ($r_{i,min},\ \forall i \in \mathcal{I}_m$). Considering that each MVNO m would require x_{ij} data rate for its UE i through BS j, we have $\sum_{j\in\mathcal{J}} x_{ij} \geq r_{i,min}$. We define the *request vector* for UE i to all J BSs as $\mathbf{x}_i \triangleq (x_{ij} : \forall j \in \mathcal{J})$. Then the total request data from MVNO m to InP n is $X_{mn} = \sum_{i\in\mathcal{I}_m}\sum_{j\in\mathcal{J}_n} x_{ij}$, and the buying matrix for all UEs of each MVNO m are given as:

$$\mathbf{x}_m = (\mathbf{x}_i :\ \forall i \in \mathcal{I}_m). \tag{1}$$

TABLE I: Key Notations

Notation	Definition
x_{ij}	Decision variable, from MVNO-demand part
$\mathbf{x}_i$	Demand bidding vector of UE i
$r_{i,min}$	UE i's minimum data rate requirement
ω_i	Scheduling weight of UE i
$\mathcal{F}_m(\omega_i, \mathbf{x}_i)$	Utility Function for MVNO m
y_{ij}	Decision variable, from InP-supply part
$\mathbf{y}_j$	Supply bidding vector of BS j
$q_{j,max}$	BS j's maximum offered data rate
σ_j	Usage state weight of BS j
$\Phi_n(\sigma_j, \mathbf{y}_j)$	Cost Function for InP n
p_{ij}	Transaction cost
d_{ij}	Relative distance between UE and BS

Similarly, we define each BS's supply as the maximum data rate offering ($q_{j,max},\ j \in \mathcal{J}_n$). InP $n \in \mathcal{N}$ wants to sell $y_{ji} \geq 0$[7] bytes of data through its BS $j \in \mathcal{J}_n$ to UE $i \in \mathcal{I}$, so the selling vector for each InP n is $\mathbf{y}_j \triangleq (y_{ij} :\ \forall i \in \mathcal{I})$ and the total offered data from InP n to MVNO m is $Y_{mn} = \sum_{i\in\mathcal{I}_m}\sum_{j\in\mathcal{J}_n} y_{ij}$. The selling matrix for all InP n are given as:

$$\mathbf{y}_n = (\mathbf{y}_j :\ \forall j \in \mathcal{J}_n). \tag{2}$$

In double auction, each bidder (both buyers and sellers) can express the subjective preference for the traded goods by using a utility function [30]. Thus, how to properly define the utility function for representing each bidders preference is an important issue for this double auction based virtual resource allocation mechanism. According to [31], the QoS requirements of each bidder can be described by its utility function. Furthermore, through maximizing the total utility within the network, the double auction method can establish a simple and automatic mechanism, that can simultaneously improve energy-efficiency and even provide the right incentives to ensure desirable QoS levels for all bidders.

For each MVNO $m \in \mathcal{M}$, in order to ensure the consistency between price and QoS level offered to its subscribed UEs $i \in \mathcal{I}_m$, we employ a two-dimension utility function $\mathcal{F}_i^m(\omega_i, \mathbf{x}_i)$ for expressing MVNO's competition during auction. This utility represents the revenues created by UEs' (and hence the profit obtained by MVNOs). In reality, UEs want to pay more for higher data rate and lower waiting time. Hence, $\omega_i \in [0, 1]$ is defined as the scheduling weight of UE, which is calculated based on the waiting time. Since higher scheduling weight, which corresponds to lower waiting time, can create more profit for MVNOs, we have:

$$\frac{\partial \mathcal{F}_i^m(\omega_i, \mathbf{x}_i)}{\partial \omega_i} > 0. \tag{3}$$

[6]In our paper, the concept of economic efficiency is defined as the *auction efficiency*, which is the maximum feasible social welfare and can be formulated as the difference between the sum of all winning bidder' valuations and the transaction cost [22].

[7]y_{ji} and y_{ij} are defined as the same parameters in this paper.

Meanwhile, motivated by the relationship between price and traffic [31], higher data rate ($\mathbf{x}_i$ is defined as the demanding data rate vector of MVNO m for its subscribed UE i) also creates more profit for MVNOs, and we have:

$$\begin{aligned}\frac{\partial \mathcal{F}_i^m(\omega_i, \mathbf{x}_i)}{\partial \mathbf{x}_i} > 0,\\ \frac{\partial^2 \mathcal{F}_i^m(\omega_i, \mathbf{x}_i)}{\partial \mathbf{x}_i^2} < 0,\end{aligned} \tag{4}$$

which means that the utility function $\mathcal{F}_i^m(\omega_i, \mathbf{x}_i)$ in data service profit dimension ($\mathbf{x}_i$) for each UE is an increasing, strictly concave and continuously twice-differentiable function of $\mathbf{x}_i$ over the range of $\mathbf{x}_i \geq 0$. This utility function is more practical for measuring the business relationship between MVNOs and its subscribed UEs (The buyers in the left side in Fig. 2). As the utilities are additive, the aggregate utility of MVNO $m \in \mathcal{M}$ is:

$$\mathcal{U}_m = \mathcal{F}_m(\mathbf{x}_m) = \sum_{i \in \mathcal{I}_m} \mathcal{F}_i^m(\omega_i, \mathbf{x}_i). \tag{5}$$

For each InP $n \in \mathcal{N}$, we also employ a two-dimension cost function $\Phi_j^n(\sigma_j, \mathbf{y}_j)$ for ensuring the consistency between the cost and service level it can offer. From the practical point of view, InP wants to exploit less spectrum and less power for transmitting data in order to reduce the cost budget. Base on the spectrum and energy consumption cost in [32], we introduce a parameter σ_j for illustrating the resource (both spectrum and energy) usage status (here the BS's usage status), where

$$\sigma_j = \begin{cases} 0, & \text{When BS } j \text{ is absolutely idle,} \\ (0,1), & \text{otherwise,} \\ 1, & \text{When BS } j \text{ is absolutely full.} \end{cases} \tag{6}$$

Parameter σ_j can also be used in the cost function for illustrating the InPs' behaviours concerning resource consumption. We define the properties of Φ_j^n over σ_j as:

$$\frac{\partial \Phi_j^n(\sigma_j, \mathbf{y}_j)}{\partial \sigma_j} \begin{cases} < 0, & \text{During low-traffic-load period,} \\ > 0, & \text{During high-traffic-load period,} \end{cases} \tag{7}$$

where the high- and low-traffic-load period are defined by the Info Controller (in Section III-A), as it can acquire the overall information from system perspective and forward the information to InPs. This definition reflects InP's preference when choosing BSs, that is, InP prefers choosing BSs with light-usage status (i.e. small σ_j value) during high-traffic-load period, and choosing BSs with rather heavy-usage status (i.e. large σ_j value) during low-traffic-load period in order to flexibly make individual switching-off decisions for rather idle BSs (i.e. BSs with the smallest σ_j value), which in reverse can bring more profit for each InP n. Besides, the difference between high- and low-traffic-load period can also help to save energy consumption, reduce cost budget and even balance the traffic load among BSs.

Meanwhile, motivated by the relationship between cost and traffic, higher data rate ($\mathbf{y}_j$ is defined as the supplying data rate vector of InP n for its BSs j) also stimulates higher cost for InPs, and we have:

$$\begin{aligned}\frac{\partial \Phi_j^n(\sigma_j, \mathbf{y}_j)}{\partial y_j} > 0,\\ \frac{\partial^2 \Phi_j^n(\sigma_j, \mathbf{y}_j)}{\partial y_j^2} > 0,\end{aligned} \tag{8}$$

which means that the cost function $\Phi_j^n(\sigma_j, \mathbf{y}_j)$ in traffic dimension ($\mathbf{y}_j$) for each BS is an positive increasing, strictly convex and continuously differentiable function of vector $\mathbf{y}_j$, and $\Phi_j^n(\sigma_j, 0) = 0$. This cost function corresponds to the business relationship between InPs and its BSs in Fig. 2. As the cost is additive, for each InP n the total cost is:

$$\Phi_n(\mathbf{y}_n) = \sum_{j \in \mathcal{J}_n} \Phi_j^n(\sigma_j, \mathbf{y}_j). \tag{9}$$

Thus the utility of each InP n is:

$$\mathbb{U}_n = -\Phi_n(\mathbf{y}_n). \tag{10}$$

In order to ensure the heterogeneity and energy efficiency among different InPs and MVNOs, we introduce a *distance-related transaction cost* [33], which includes the costs associated with signaling, backhaul, etc. When MVNO $m \in \mathcal{M}$ purchases data from InP $n \in \mathcal{N}$, a transaction cost is incurred. Thus, even if two InPs provide the same speed of data rate, they may still be heterogeneous due to these transaction-related costs.

We define $p_{ij} > 0$ ($i \in \mathcal{I}_m, j \in \mathcal{J}_n$) as the transaction cost between MVNO m and InP n. It is the price per unit of data rate and charged by the auctioneer. As we have the relationship: SNR $= \frac{c_{ij}|h_0|^2}{d_{ij}^{\alpha} N_0}$ [34] (where c_{ij} is the power consumption, d_{ij} is the relative distance between receiver and transmitter, $|h_0|^2$ is the complex Gaussian channel coefficient, α is the free space path-loss exponent and N_0 is the additive white Gaussian noise.), when the transmitted SNR remains the same, power consumption c_{ij} can be redefined as:

$$c_{ij} \propto \frac{N_0}{|h_0|^2} \cdot d_{ij}^{\alpha}. \tag{11}$$

We further define the transaction cost as a proportional to the power consumption during transmission, we have: $p_{ij} \propto c_{ij} \propto d_{ij}^{\alpha}$. For simplification, the transaction cost p_{ij} is defined as having a direct relationship with the relative distance d_{ij} and path loss α between UE i and BS j:

$$p_{ij} = \theta \cdot d_{ij}^{\alpha}, \tag{12}$$

where $\theta \propto \frac{N_0}{|h_0|^2} > 0$ is a predefined parameter and calculated by the RA-V controller according to the actual situation. In this work, it is assumed to be known as common knowledge. T_{mn} is denoted as the total transmitted data amount between MVNO m and InP n:

$$T_{mn} = \sum_{i \in \mathcal{I}_m} \sum_{j \in \mathcal{J}_n} \min(x_{ij}, y_{ij}). \tag{13}$$

Thus the total transaction cost is:

$$\mathcal{T}_{total} = \sum_{m \in \mathcal{M}} \sum_{n \in \mathcal{N}} p_{ij} T_{mn}. \tag{14}$$

Therefore, the transaction cost is indirectly related to the power consumption during the data transmission, which means the RA-V controller can take charge of the energy-efficiency by adjusting p_{ij}. We will further discuss it in the simulation section.

C. Social Welfare Maximization

To make auction more economic efficiency, we expect that the auction results can not only stimulate the resource sharing but also improve certain economic performance, i.e. feasible social welfare, which can be formulated as the difference between the sum of all winning bidders' valuations and the transaction costs [22]. As it is clear that the objectives of both MVNOs and InPs are conflicting, if they decide independently, it will be very difficult to reach an agreement (x_{ij} and y_{ij}). For the sake of notational simplicity, we rewrite the decision variables for the RA-V controller as:

$$\mathbf{x} \triangleq (\mathbf{x}_m : \forall m \in \mathcal{M}) = (x_{ij} : \forall i \in \mathcal{I},\ \forall j \in \mathcal{J}), \tag{15}$$

$$\mathbf{y} \triangleq (\mathbf{y}_n : \forall n \in \mathcal{N}) = (y_{ij} : \forall j \in \mathcal{J},\ \forall i \in \mathcal{I}). \tag{16}$$

In order to maintain fairness and satisfy the heterogeneous QoS requirements, the RA-V controller tries to find optimal $\mathbf{x}$ and $\mathbf{y}$ by solving the Social Welfare Optimization (**SWO**) problem:

$$\textbf{SWO}:\ \max_{(\mathbf{x},\mathbf{y})} \sum_{m\in\mathcal{M}} \mathcal{U}_m + \sum_{n\in\mathcal{N}} \mathbb{U}_n - \mathcal{T}_{total}. \tag{17}$$

$$s.t.\quad A1: \sum_{j\in\mathcal{J}} x_{ij} \geq r_{i,min},\ \forall i \in \mathcal{I}, \tag{18}$$

$$A2: \sum_{i\in\mathcal{I}} y_{ij} \leq q_{j,max},\ \forall j \in \mathcal{J}, \tag{19}$$

$$A3: y_{ij} \geq x_{ij},\ \forall i \in \mathcal{I},\ \forall j \in \mathcal{J}, \tag{20}$$

$$A4: y_{ij} \geq 0,\ x_{ij} \geq 0,\ \forall i \in \mathcal{I},\ \forall j \in \mathcal{J}. \tag{21}$$

Constraints (18) indicate that the amount of data that each MVNO decides to bid should satisfy the demanding QoS requirements of UEs. Constraints (19) indicate that the amount of offered data cannot exceed the available amount of each BS for InPs. In the double auction problem, we try to find a competitive equilibrium, which is a situation where the supply equals to the demand from an economist's perspective, i.e. $x_{ij} = y_{ij}$.

Through the definition of T_{mn} in (13), we can see that the total transmitted data amount depends on decision variables $\mathbf{x}$ and $\mathbf{y}$, especially the relationship between them. Furthermore, it is obvious that at the equilibrium, it will hold ($y_{ji} = x_{ij},\ \forall i \in \mathcal{I}, \forall j \in \mathcal{J}$) from constraints (20). So we can define:

$$T_{mn} = \frac{\sum_{i\in\mathcal{I}_m}\sum_{j\in\mathcal{J}_n}(x_{ij}+y_{ij})}{2},\ \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \tag{22}$$

which means that the total transmitted data amount depends both on demand $\mathbf{x}$ and supply $\mathbf{y}$, i.e. MVNOs and InPs will play equally important roles in achieving the social welfare maximization (17).

Therefore, we can rewrite the objective function in (17) as:

$$\mathcal{Z}(\mathbf{x},\mathbf{y}) = \sum_{m\in\mathcal{M}} \mathcal{F}_m(\mathbf{x}) - \sum_{n\in\mathcal{N}} \Phi_n(\mathbf{y}) - \frac{p_{mn}}{2}\sum_{m\in\mathcal{M}}\sum_{n\in\mathcal{N}}(\mathbf{x}+\mathbf{y}). \tag{23}$$

According to the defined concavity and convexity characteristics in (4) and (8), we can clearly see that the objective function in **SWO** is strictly concave in $(\mathbf{x}^*, \mathbf{y}^*)$.

Theorem 1. *Social welfare maximization problem SWO has a unique optimal solution* $(\mathbf{x}^*, \mathbf{y}^*)$.

Proof. The proof is intuitive. As the objective function in **SWO** is strictly concave in $(\mathbf{x}, \mathbf{y})$, and the feasible region defined by constraints (18)-(21) is convex, **SWO** has a unique optimization solution $(\mathbf{x}^*, \mathbf{y}^*)$ subject to constraints (18)-(21). □

V. ITERATIVE DOUBLE AUCTION ALGORITHMS

As it is infeasible for the RA-V controller to derive the optimal SWM solution through solving the problem above directly, due to the hidden information to RA-V controller, i.e. the valued weights of user priority ω_i, σ_j and utility functions $\mathcal{F}_m$, Φ_n. Moreover, finding the optimal demand-supply equilibrium by exhaustive search is NP-hard [18]. Therefore, an **Iterative Double Auction** (I-DA) algorithm is proposed to induce the buyers (MVNOs) and sellers (InPs) to truthfully reveal their needs, derive the hidden information, enhance the scalability of the network and accelerate the signalling and information exchange.

A. Problem Transformation with Shadow Price

Shadow price is a method for illustrating the marginal utility of constrained optimization in economics [35]. It is proposed here for eliciting the asymmetric information of both $\mathcal{F}_m$ and Φ_n. As the primal **SWO** problem admits a unique optimal solution, we first analyze it from the viewpoint of the Lagrangian dual problem with shadow price vector $(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu})$:

$$\begin{aligned}\mathcal{L}(\mathbf{x},\mathbf{y},\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu}) = & \sum_{m\in\mathcal{M}} \mathcal{F}_m(\mathbf{x}_m) - \sum_{n\in\mathcal{N}} \Phi_n(\mathbf{y}_n) \\ & - \sum_{m\in\mathcal{M}}\sum_{n\in\mathcal{N}} \frac{p_{ij}}{2}(\mathbf{x}_m + \mathbf{y}_n) \\ & - \sum_{i\in\mathcal{I}} \lambda_i (r_{i,min} - \sum_{j\in\mathcal{J}} x_{ij}) \\ & - \sum_{j\in\mathcal{J}} \mu_j (\sum_{i\in\mathcal{I}} y_{ij} - q_{j,max}) \\ & - \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} \nu_{ij}(x_{ij} - y_{ij}),\end{aligned} \tag{24}$$

where $\boldsymbol{\lambda} \triangleq (\lambda_i \geq 0 : \forall i \in \mathcal{I})$, $\boldsymbol{\mu} \triangleq (\mu_j \geq 0 : \forall j \in \mathcal{J})$ are the vector of Lagrangian multipliers corresponding to constraints (18) and (19) separately, and $\boldsymbol{\nu} \triangleq (\nu_{ij} \geq 0 : \forall i \in \mathcal{I}, \forall j \in \mathcal{J})$ is the matrix of Lagrangian multipliers for constraints (20). According to [36], we define the dual objective $g(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu})$ as an unconstrained maximization of Lagrangian (24):

$$g(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu}) = \max_{\mathbf{x},\mathbf{y}} \mathcal{L}(\mathbf{x},\mathbf{y},\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu}) \tag{25}$$

Algorithm 2 I-DA: Bidding Strategies for MVNOs

Obtaining current iteration price vector: $[\boldsymbol{\lambda}^{(t)}, \boldsymbol{\mu}^{(t)}, \boldsymbol{\nu}^{(t)}]$
for all $m \in \mathcal{M}$ **do**
  for all $i \in \mathcal{I}_m$ **do**
    Assign scheduling weight ω_i for all UE $i \in \mathcal{I}_m$
    Calculate $x_{ij}^{(t)}$ according to (B1): $\frac{\partial \mathcal{F}_i^m(\omega_i, \mathbf{x}_i^{(t)})}{\partial x_{ij}} = \frac{p_{ij}}{2} - \lambda_i^{(t)} + \nu_{ij}^{(t)}$
    for all $j \in \mathbb{J}$ **do**
      if (B3): $\sum_{j \in \mathcal{J}} x_{ij}^{(t)} \geq r_{i,min}$ **then**
        $\mathbf{x}_i^{(t)} \leftarrow x_{ij}^{(t)}$
      end if
    end for
  end for
  $\boldsymbol{\varpi}_m^{(t)} = (\mathbf{x}_i^{(t)} : \forall i \in \mathcal{I}_m)$
end for
Uploading bidding strategies $\boldsymbol{\varpi}_m^{(t)}$ to RA-V controller

The dual optimization problem is:

$$\begin{aligned} &\min \ g(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu}) \\ &s.t. \ \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu} \geq 0 \end{aligned} \tag{26}$$

The basic idea in finding the global optimum is to solve the Lagrangian for each set of non-negative and fixed $(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu})$. The solution to the original problem can be found by a nested bisection search in the $(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu})$-space. It can be shown that this this kind algorithm has a computational complexity that is exponential in the number of UEs M and BSs N. Consequently, the purpose of this paper is to find low-complexity ways to eliminate the exponential complexity.

B. The Bidding Strategies

The primal-dual problem above satisfies the necessary and sufficient Karush-Kuhn-Tucker (KKT) conditions. The KKT conditions that yield the optimal dual variables (shadow price) $\boldsymbol{\lambda}^*, \boldsymbol{\mu}^*, \boldsymbol{\nu}^*$ and optimal primal variables $\mathbf{x}^*$, $\mathbf{y}^*$ for the problem **SWO** are given by the following set of equations:

$$\begin{aligned} &(B1): \frac{\partial \mathcal{F}_i^m(\omega_i, \mathbf{x}_i^*)}{\partial x_{ij}} = \frac{p_{ij}}{2} - \lambda_i^* + \nu_{ij}^*; \\ &(B2): \frac{\partial \Phi_j^n(\sigma_j, \mathbf{y}_j^*)}{\partial y_{ij}} = -\frac{p_{ij}}{2} - \mu_j^* + \nu_{ij}^*; \\ &(B3): \sum_{j \in \mathcal{J}} x_{ij}^* = r_{i,min}; \\ &(B4): \sum_{i \in \mathcal{I}} y_{ij}^* = q_{j,max}; \\ &(B5): x_{ij}^* = y_{ij}^*. \end{aligned} \tag{27}$$

where $x_{ij}^*, y_{ij}^*, \lambda^*, \mu^*, \nu^* \geq 0$ are the global maximizers for the social welfare maximization problem **SWO**.

We can see that (B1), (B3), (B5) together combine the optimization solutions for MVNOs, (B2), (B4), (B5) together combine the optimization solutions for InPs, and (B5) holds the system equilibrium for both MVNOs and InPs. We assume that the RA-V controller is the broker, which derives proper pricing schemes to induce bidders biding truthfully and eventually achieve system equilibrium. Through (B1) and (B2), we can see that the right-side of the equation consists of only price-related definitions, which is linear combination of transaction cost and shadow price of the constraints. Therefore, we define pricing scheme as:

$$\begin{cases} \text{Payment of MVNO-m:} & \mathbf{x}_m \cdot \sum_{i \in \mathcal{I}_m} (\frac{p_{ij}}{2} - \lambda_i + \nu_{ij}), \\ \text{Reimbursement of InP-n:} & \mathbf{y}_n \cdot \sum_{j \in \mathcal{J}_n} (-\frac{p_{ij}}{2} - \mu_j + \nu_{ij}). \end{cases} \tag{28}$$

We take MVNO-m as reference, the left-side of the (B1) is first-order differential of valuation function, hence, a sub-problem based on the KKT conditions for MVNO-m to produce optimum bidding strategies is established as:

$$\begin{aligned} \text{MVNO-m}: \ &\max_{\boldsymbol{\varpi_m}} \mathcal{F}_m(\mathbf{x}_m) - \sum_{i \in \mathcal{I}_m} (\frac{p_{ij}}{2} - \lambda_i + \nu_{ij}) \cdot \mathbf{x}_m \\ &s.t. \ \boldsymbol{\varpi_m} \geq 0, \end{aligned} \tag{29}$$

where $\boldsymbol{\varpi_m}$ are the bids of MVNO m:

$$\boldsymbol{\varpi_m} \triangleq (\mathbf{x}_i^o : \forall i \in \mathcal{I}_m)|_{\text{MVNO-m}} = \boldsymbol{\varpi_m}(\omega_i, p_{ij}, \lambda_i, \nu_{ij}). \tag{30}$$

We can see that the objective function for MVNO-m is strictly concave. The optimal bidding strategy is its Jacobian matrix, which is the same with (B1). $(\frac{p_{ij}}{2} - \lambda_i + \nu_{ij})$ is the unit price charged by the RA-V controller.

With the same analysis method, we can obtain the sub-problem for InPs to produce bidding strategies as:

$$\begin{aligned} \text{InP-n}: \ &\max_{\boldsymbol{\beta_n}} \sum_{j \in \mathcal{J}_n} (-\frac{p_{ij}}{2} - \mu_j + \nu_{ij}) \cdot \mathbf{y}_n - \Phi_n(\mathbf{y}_n), \\ &s.t. \ \boldsymbol{\beta_n} \geq 0, \end{aligned} \tag{31}$$

where $\boldsymbol{\beta_n}$ is the bids of InP n and:

$$\boldsymbol{\beta_n} \triangleq (\mathbf{y}_j^o : \forall j \in \mathcal{J}_n)|_{(\text{InP-n})} = \boldsymbol{\beta_n}(\sigma_j, p_{ij}, \mu_i, \nu_{ij}). \tag{32}$$

The price $(-\frac{p_{ij}}{2} - \mu_j + \nu_{ij})$ is the reimbursement RA-V controller refund for InPs which participate in the double auction. As the objective function in InP-n is concave, the optimal bidding strategy for InP-n is also (B2).

We can see that the price charged and the reimbursement in this scheme not only reflect the BS's capacity constraints, but also the UE's demand and system transaction cost.

As the MVNOs and InPs do not know each other's valuation function nor the UEs and BSs' weights, we calculate the bids, iteration by iteration, to gradually achieve a market equilibrium. We have the detailed algorithms for producing optimal bidding strategies for both MVNOs and InPs in Algorithm 2 and Algorithm 3 separately. For each MVNO, after obtaining the current iteration price vector $[\boldsymbol{\lambda}^{(t)}, \boldsymbol{\mu}^{(t)}, \boldsymbol{\nu}^{(t)}]$ and the assigned weights ω_i of its subscribed UEs, MVNO calculates its bidding strategies $\boldsymbol{\varpi_m}$ according to their true valuation of bids: (4). For each InP, after obtaining the current iteration price vector $[\boldsymbol{\lambda}^{(t)}, \boldsymbol{\mu}^{(t)}, \boldsymbol{\nu}^{(t)}]$, we also need to choose the proper valuation function $\Phi_n(\sigma_j)$ for distinguishing the high-traffic-load period and low-traffic-load period in order to save OpEx and CapEx. This is specified in Line 2 in Algorithm 3. For solving InP-n, we use nearly the same process as with solving MVNO-m.

Algorithm 3 I-DA: Bidding Strategies for InPs

```
Obtaining current iteration shadow price: [λ^(t), μ^(t), ν^(t)], Obtaining current traffic-load mode, usage-state and choose suitable valuation function Φ_n(σ_j) according to high/low-traffic load
for all n ∈ N do
    for all j ∈ J_n do
        Assign usage-state weight σ_j for all BS j
        Calculate y_ij^(t) according to (B2): ∂Φ_j^n(σ_j, y_j^(t))/∂y_ij^(t) = −p_ij/2 − μ_j^(t) + ν_ij^(t)
        for all i ∈ I do
            if (B4): Σ_{i∈I} y_ij^(t) ≤ q_{j,max} then
                y_j^(t) ← y_ij^(t)
            end if
        end for
    end for
    β_n^(t) = (y_j^(t) : ∀j ∈ J_n)
end for
Uploading bidding strategies β_n^(t) to RA-V controller
```

Algorithm 4 I-DA: Resource Allocation by RA-V controller

```
Initialize λ^(0), μ^(0), ν^(0)
Obtaining current bidding strategies from MVNO: ϖ_m^(t) and InP: β_n^(t)
if (B5): y_ij^(t) ≥ x_ij^(t) then
    if y_ij^(t) − x_ij^(t) ≤ ε then
        Checking Termination Condition
        if |F_m^(t) − F_m^(t−1)| ≤ ε_m and |Φ_n^(t) − Φ_n^(t−1)| ≤ ε_n then
            Set Convergence ← 1
        end if
    end if
end if
while (Convergence! = 1) do
    Update price vector [λ^(t+1), μ^(t+1), ν^(t+1)] by sub-gradient method according to (33)
end while
textbfOutput x, y, λ, μ, ν.
```

C. Duality Gap

Through (B5), we can infer that at the equilibrium we have $\mathbf{x}^* = \mathbf{y}^*$, which means that the supply equals the demand. So for the RA-V controller, we need to solve the problem below to obtain social welfare maximization:

$$\begin{aligned} \text{RA-V: } \min\ & |x_{ij} - y_{ij}|, \\ s.t.\ & x_{ij} \leq y_{ij}. \end{aligned} \tag{33}$$

We define $[\varepsilon_m, \varepsilon_n, \varepsilon]$ as the **convergence** vector. ε is defined as the system equilibrium,, and when it has been satisfied, the supply will equal the demand. ε_m and ε_n are defined as the bidding equilibrium, when they are satisfied, MVNOs and InPs obtain their own maximal profit no matter how they change their bidding strategies. If the calculated bidding strategies satisfy the **convergence** vector, the I-DA algorithms terminate; otherwise the I-DA algorithms continue, and we need a mechanism for updating the price vector $[\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu}]$. Here we update the dual variables $[\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu}]$ by using a sub-gradient descent method:

$$\begin{aligned} \lambda_i^{(t+1)} &= \left(\lambda_i^{(t)} - \Delta\lambda \frac{\partial \mathcal{L}(\cdot)}{\partial \lambda_i}\right)^+, \ \forall i \in \mathcal{I}, \\ \mu_j^{(t+1)} &= \left(\mu_j^{(t)} - \Delta\mu \frac{\partial \mathcal{L}(\cdot)}{\partial \mu_j}\right)^+, \ \forall j \in \mathcal{J}, \\ \nu_{ij}^{(t+1)} &= \left(\nu_{ij}^{(t)} - \Delta\nu \frac{\partial \mathcal{L}(\cdot)}{\partial \nu_{ij}}\right)^+, \ \forall i \in \mathcal{I}, \forall j \in \mathcal{J}. \end{aligned} \tag{34}$$

where $()^+$ denotes the projection onto the non-negative orthant and ensures that feasibility constraints $\lambda_i^{(t+1)} \geq 0$, $\mu_j^{(t+1)} \geq 0$ and $\nu_{ij}^{(t+1)} \geq 0$. In order to simplify the overall parameter setting, we set here $\Delta\lambda = \Delta\mu = \Delta\nu = \Delta$.

As the objective function in **SWO** is strictly concave and the constraints are compact and convex, the results guarantee that the primal problem (17) and the dual problem (26) have the same solution [36], i.e. the duality gap between the primal and dual function can be assumed negligible. The details of the entire I-DA mechanism are described as **Algorithm 2,3,4**, where Algorithm 2 and Algorithm 3 are executed synchronously to compute the optimal bids (29) and (31) for both MVNOs and InPs in each round. Algorithm 4 is executed by SDV controller to determine the proper resource allocation $\mathbf{x}^*$ and $\mathbf{y}^*$ iteration by iteration until converges to ε.

D. Convergence Analysis

Theorem 2. *The proposed I-DA algorithm converges to the optimal solution globally.*

Proof: There exists Lyapunov function $G(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu})$ for the proposed I-DA algorithm

$$\begin{aligned} G(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu}) &= \sum_{i\in\mathcal{I}} \frac{(\lambda_i - \lambda_i^*)^2}{2} + \sum_{j\in\mathcal{J}} \frac{\left(\mu_j - \mu_j^*\right)^2}{2} \\ &+ \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \frac{\left(\nu_{ij} - \nu_{ij}^*\right)^2}{2}, \end{aligned} \tag{35}$$

which is locally positive-definite in the optimal point $(\boldsymbol{\lambda}^*, \boldsymbol{\mu}^*, \boldsymbol{\nu}^*)$:

$$G(\boldsymbol{\lambda}^*, \boldsymbol{\mu}^*, \boldsymbol{\nu}^*) = 0,\ G(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu}) \geq 0,\ \forall \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu} \in \mathbb{R}^+ \setminus \{\boldsymbol{\lambda}^*, \boldsymbol{\mu}^*, \boldsymbol{\nu}^*\}, \tag{36}$$

and with time derivative strictly non-positive:

$$\frac{dG(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu})}{dt} \leq 0. \tag{37}$$

Hence, according to [37], the proposed I-DA algorithm converge to the global optimal.

The detailed proof is in Appendix A ■

VI. The Economic Properties

In this section, we prove the I-DA mechanism observes the properties of individual rationality, truthfulness and balanced budget proposed in Section IV-A.

Lemma 1. *The I-DA mechanism is individual-rational, i.e. each buyers and each sellers utility is no less than its utility from nonparticipation for all possible outcomes.*

Proof: The bids $\boldsymbol{\varpi_m}$ and $\boldsymbol{\beta_n}$ always satisfy

$$\begin{aligned} \mathbf{B}_m &= \mathcal{F}_m(\mathbf{x}_m^o) - \sum_{i\in\mathcal{I}_m} (\frac{p_{ij}}{2} - \lambda_i + \nu_{ij}) \cdot \mathbf{x}_m^o \geq 0, \\ \mathbb{B}_n &= \sum_{j\in\mathcal{J}_n} (-\frac{p_{ij}}{2} - \mu_j + \nu_{ij}) \cdot \mathbf{y}_n^o - \Phi_n(\mathbf{y}_n^o) \geq 0. \end{aligned} \tag{38}$$

Where we can infer that when they are not participating in the auction, the payoff for any MVNO and InP will be zero, as $\mathbf{B}_m(0) = 0$ and $\mathbb{B}_n(0) = 0$. If they participate in the auction, the optimal bidding strategies $\boldsymbol{\varpi_m}$ and $\boldsymbol{\beta_n}$ always lead to positive utility for any MVNO and InP, i.e. $\mathbf{B}_m(\mathbf{x}_m^o) > 0$ and $\mathbb{B}_n(\mathbf{y}_n^o) > 0$.

The detailed proof is in Appendix B. ∎

Lemma 2. *Reporting valuation turthfully is weakly dominated stategy for both buyers and sellers, i.e. bidders (MVNOs and InPs) cannot misreport their bidding price to increase the utility gain.*

Proof: During each iteration, the best strategy of a rational bidder is trying to maximize one's own gain. We have three cases for explaning the best bidding strategies.

Case I: $\mathcal{F}_m(\mathbf{x}_m) - \sum_{i\in\mathcal{I}_m}(\frac{p_{ij}}{2} - \lambda_i + \nu_{ij}) \cdot \mathbf{x}_m < 0$, $\left(\sum_{j\in\mathcal{J}_n} (-\frac{p_{ij}}{2} - \mu_j + \nu_{ij}) \cdot \mathbf{y}_n - \Phi_n(\mathbf{y}_n) < 0\right)$. MVNOs (InPs) won't participate the bidding because of negative profit.

Case II: $\mathcal{F}_m(\mathbf{x}_m) - \sum_{i\in\mathcal{I}_m}(\frac{p_{ij}}{2} - \lambda_i + \nu_{ij}) \cdot \mathbf{x}_m = 0$, $\left(\sum_{j\in\mathcal{J}_n} (-\frac{p_{ij}}{2} - \mu_j + \nu_{ij}) \cdot \mathbf{y}_n - \Phi_n(\mathbf{y}_n) = 0\right)$. The I-DA mechanism ensures the voluntary participation of the bidders since they are guaranteed to have at least zero net utility for all possible market outcomes.

Case III: $\mathcal{F}_m(\mathbf{x}_m) - \sum_{i\in\mathcal{I}_m}(\frac{p_{ij}}{2} - \lambda_i + \nu_{ij}) \cdot \mathbf{x}_m > 0$, $\left(\sum_{j\in\mathcal{J}_n} (-\frac{p_{ij}}{2} - \mu_j + \nu_{ij}) \cdot \mathbf{y}_n - \Phi_n(\mathbf{y}_n) > 0\right)$. As $\mathcal{F}_m(\mathbf{x}_m)$ and $-\Phi_n(\mathbf{y}_n)$ are strictly concave, we can infer that, in each iteration the best response for both MVNO and InP satisfies:

$$\begin{aligned} &\frac{\partial \mathcal{F}_i^m(\mathbf{x}_{ij}^{(t)})}{\partial x_{ij}} - \left(\frac{p_{ij}}{2} - \lambda_i^{(t)} + \nu_{ij}^{(t)}\right) = 0,\ \forall i \in \mathcal{I}, \forall j \in \mathcal{J}, \\ &\left(-\frac{p_{ij}}{2} - \mu_j^{(t)} + \nu_{ij}^{(t)}\right) - \frac{\partial \Phi_j^n(\mathbf{y}_{ij}^{(t)})}{\partial y_{ij}^{(t)}} = 0,\ \forall i \in \mathcal{I}, \forall j \in \mathcal{J}. \end{aligned} \tag{39}$$

By observing the bids, we can see that the bidders (MVNOs and InPs) submit their currently optimal bids according to the iteration price vector $(p_{ij}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{\nu})$. Therefore, even though the RA-V controller does not know the true valuation function of both MVNOs and InPs, which still submit the socially optimal bids of the market, it can eventually lead to social welfare maximization. ∎

Lemma 3. *The RA-V controller can take charge of its own payoff by changing the transaction cost p_{ij}, i.e. the I-DA is weakly budget balanced.*

Proof: The RA-V controller's budget balance $\Theta(\boldsymbol{\varpi_m}, \boldsymbol{\beta_n})$ is defined as:

$$\begin{aligned} \Theta(\boldsymbol{\varpi_m}, \boldsymbol{\beta_n}) &= \sum_{m\in\mathcal{M}} \sum_{i\in\mathcal{I}_m} (\frac{p_{ij}}{2} - \lambda_i^o + \nu_{ij}^o) \cdot \mathbf{x}_m^o \\ &\quad - \sum_{n\in\mathcal{N}} \sum_{j\in\mathcal{J}_n} (-\frac{p_{ij}}{2} - \mu_j^o + \nu_{ij}^o) \cdot \mathbf{y}_n^o \end{aligned} \tag{40}$$

which is the difference between the charge of all MVNOs and reimbursement of all InPs. According to (B3) (B4) and (B5), at the equilibrium we have

$$\Theta(\boldsymbol{\varpi_m}, \boldsymbol{\beta_n}) = \underbrace{\sum_{i\in\mathcal{I}} r_{i,min}\left(\frac{p_{ij}}{2} - \lambda_i^o\right)}_{demand} + \underbrace{\sum_{j\in\mathcal{J}} q_{j,max}\left(\frac{p_{ij}}{2} + \mu_j^o\right)}_{offer}. \tag{41}$$

We can see that the *offer* part is strictly positive. Therefore as long as $\left(\frac{p_{ij}}{2} - \lambda_i\right) \geq 0$, the I-DA mechanism is strictly weakly budget balanced. Through the definition of p_{ij} and the sub-gradient descend method for updating Lagrangian multipliers $\boldsymbol{\lambda}$, the *demand* part is mostly positive. If it is not positive, then it can also be adjusted by the RA-V controller to make it positive. Therefore, the RA-V can hold the auction without an outside subsidy. ∎

VII. Performance Evaluation

In this section, we provide the simulation results to illustrate theoretical analysis and the performance of the proposed I-DA algorithm.

A. Parameter Setting

We consider a scenario where there are two InPs and two MVNOs operating within the same geographical area. They all are controlled by SDV controllers and the system resources (including spectrum, time-slots, core networks etc.) are sliced into TFs, which can be specified as "data rate" and assumed to be with a unit of (Mbps). The valuation functions of both MVNOs and InPs are respectively defined as:

$$\mathcal{F}_m = 20 \cdot \sum_{i\in\mathcal{I}_m} \log_{\rho_m}\left(e^{\omega_i} \cdot (\mathbf{x}_i + 1)\right) \tag{42}$$

$$\Phi_n = \begin{cases} 2\cdot\phi_n \sum_{j\in\mathcal{J}_n} \left(e^{\frac{(1-\sigma_j)\mathbf{y}_j}{\phi_n}} - 1\right), & \text{Low-traffic-load Period,} \\ 2\cdot\phi_n \sum_{j\in\mathcal{J}_n} \left(e^{\frac{\sigma_j\cdot\mathbf{y}_j}{\phi_n}} - 1\right), & \text{High-traffic-load Period.} \end{cases} \tag{43}$$

We consider three cases here, where the first two separately corresponds to the high and low-traffic-load period defined in (7). The remaining one is benchmark case, which allows

TABLE II: The Simulating Parameters

Parameter	Case I: High-traffic-load period	Case II: Low-traffic-load period	Benchmark
MVNO: ρ_m	[2, 5]	[2, 5]	$\rho_m = 2,\ \forall m \in \mathcal{M}$
MVNO: $r_{i,min}$	10 (Mbps)	5 (Mbps)	10 (Mbps)
MVNO1: ω_i	[0.5,0.3,0.2](3 UEs)	[0.33,0.16,0.79,0.31,0.53](5 UEs)	$\omega_i = 0.5,\ \forall i \in \mathcal{I}$
MVNO2: ω_i	[0.6,0.4](2 UEs)	[0.17,0.60,0.26,0.65,0.69](5 UEs)	
InP: ϕ_n	[20,30]	[20,30]	$\phi_n = 20,\ \forall n \in \mathcal{N}$
InP: $q_{j,max}$	[20] (Mbps)	[20] (Mbps)	[10] (Mbps)
InP1: σ_j	[0.5,0.3](BS1, BS2)	[0.5,0.1](BS1, BS2)	$\sigma_j = 0.5,\ \forall j \in \mathcal{J}$
InP2: σ_j	[0.6] (BS3)	[0.9](BS3)	

expansion of MVNOs, UEs InPs and BSs with unified parameters setting. The detailed parameters are listed in Table II.

To generalize the assessment of our proposal, in Case I, we assume that the pre-negotiated transaction cost is $p_{ij} = 2$ (i.e. no energy consumption considered). In Case II, we consider UEs are randomly located within one 200m×200m geographical area, and we take the definition in (12) to illustrate distance-related transaction cost, where

$$p_{ij} = \begin{cases} 10^{-3} \times d_{ij}^2, & \alpha = 2, \\ 10^{-7} \times d_{ij}^4, & \alpha = 4. \end{cases} \tag{44}$$

B. Effects of two-dimensional utility functions

Fig. 3 illustrates the UE-BS association in Case I. It specifies the final allocated flow-relationship between UEs and BSs, which reflects the impact of parameter ω_i, σ_j, Φ_n and $\mathcal{F}_m$ (defined in (42) and (43)) produced during double auction. In order to illustrate their impact more clearly, we have Fig. 4, which shows the impact of scheduling weight ω_i and usage-state weight σ_j separately for the evolution of MVNOs and InPs' demand x_{ij} and supply y_{ij}. This scenario is in the high-traffic-load period (Case I), where we can see the bidding strategies change accordingly. For MVNOs, we take the demand changing of UE1 and UE3 to BS2 (x_{12} and x_{32}) as reference[8]. As shown, UE1 with higher scheduling requirement ($\omega_1 = 0.5$) has a higher priority when bidding. MVNO1 will increase demand (x_{12}) accordingly and meanwhile decrease the demand (x_{32}) of UE3 ($\omega_3 = 0.2$) iteration by iteration. Same phenomenon can be seen with InPs. It is obvious that BS2 will increase the bid (y_{22}) and BS1 will decrease the bid (y_{21}) separately in order to maintain the utility, and eventually balance the load during high-traffic-load period. This phenomenon demonstrates that the proposed double auction mechanism can offer the priority consistency between price and QoS level proposed in [11].

In Fig. 5, we evaluate bidding gap $(X_{2n} - Y_{2n})$ between demand from MVNO2 (X_{2n}) and supply from InP "n[9]" to MVNO2 (Y_{n2}) (also described as (Y_{2n})) to prove the effectiveness of the I-DA algorithm (at equilibrium it holds $(X_{2n} - Y_{2n}) \to 0$), where:

$$\begin{aligned} X_{21} &= x_{41} + x_{42} + x_{51} + x_{52}, \quad X_{22} = x_{43} + x_{53}, \\ Y_{21} &= y_{41} + y_{42} + y_{51} + y_{52}, \quad\ Y_{22} = y_{43} + y_{53}. \end{aligned} \tag{45}$$

[8]UE1 and UE3 are chosen as reference because they have bigger difference between weights and are all belong to MVNO1, which means they have the same valuation for bidding except for scheduling weight.

[9]$n = 1$ means the demand/supply between MVNO2 and InP1 and $n = 2$ means demand/supply between MVNO2 and InP2.

As shown, at the beginning, the bidding gap $(X_{2n} - Y_{2N})$ of both situation is nearly the same, especially before the 5^{th} iteration. After re-negotiating the transaction cost, ($p_{22} = 2 \to 10$, i.e. transaction cost between MVNO2 and InP2 is increased from 2 to 10), MVNO2, InP1 and InP2 change their bidding strategies accordingly, especially between the 5^{th} and 10^{th} iteration: as the price ($\Delta p_{22} = 10 - 2 = 8$) between MVNO2 and InP2 increased, in order to ensure the demanding QoS amount for its subscribed UE3, MVNO2 needs to increase its demand for InP1 X_{21} and significantly decrease the demand for InP2 X_{22}. This phenomenon demonstrates that at equilibrium, demand X_{mn} equals to supply Y_{mn}, as shown by the analysis in Section V-C.

C. Convergence of the proposed I-DA mechanism

We evaluate the performance of the proposed double auction mechanism by comparing two benchmark schemes. The first algorithm is the central control algorithm, where RA-V controller allocates the virtual resource by only considering the amount of demand and offer. In this case, information of InPs and MVNOs utility function is hidden to the RA-V controller, regardless of ω_i and σ_j. The second algorithm is the IA-PV algorithm proposed in [34] for achieving higher system throughput by running a combinatorial auction with uni-flow transmission. For accuracy, we also provide benchmark case[10] for convergence comparison.

Fig. 6 illustrates the comparison. As shown in this figure, the proposed I-DA algorithm outperforms the other two benchmark schemes: not only the total system welfare is higher but also the convergence speed is quicker. This phenomenon is even obvious in the benchmark case (the top one). Fig. 5 also illustrates the convergence of $\mathbf{x}_i$ and $\mathbf{y}_j$. Here we see that the gap between the requested demand and offered traffic gradually converges to zero, which satisfies condition B5 in (27). This means that the MVNOs and InPs agree on the amount of data and negotiated transaction cost p_{ij}, as well as on the RA-V controller's central control.

D. Energy Efficiency

Fig. 7 illustrates the relationship between EE and different definition of transaction cost p_{ij} with increasing UE number. Energy efficiency is defined as EE $= \frac{\sum_{i \in \mathcal{I}} y_{i1}}{\sum_{i \in \mathcal{I}} p_{i1}}$ with unit of (kbits/Joure) for reference. We take 3 different definitions of p_{ij} for showing their impact on EE. Compare the blue one

[10]For comparison, we only consider two MVNOs and two InPs in this benchmark case

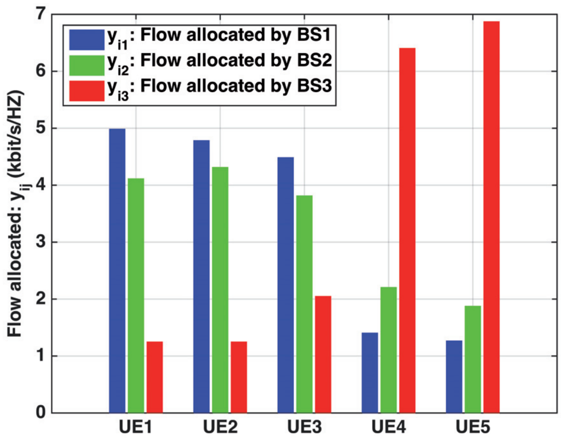


Fig. 3: UE-BS association in Case I, where demand x_{ij} equals to supply y_{ij}

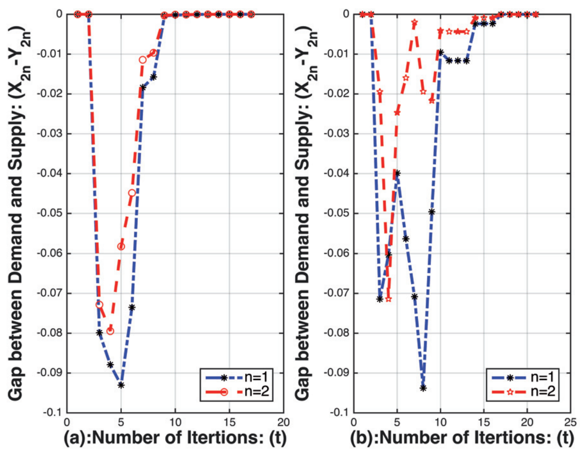


Fig. 5: Demand and supply gap ($x_{ij} - y_{ij}$) evolution with p_{22} increases.

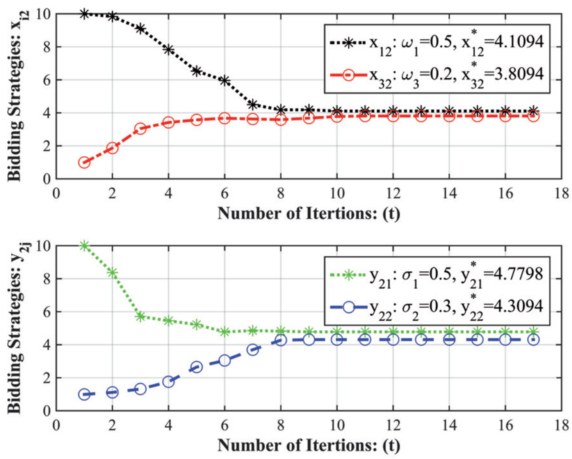


Fig. 4: The impact of UEs' scheduling weight ω_i and BSs' usage-state weight σ_j.

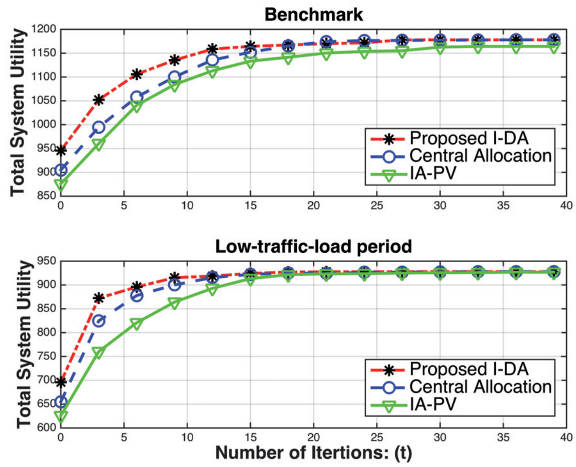


Fig. 6: The comparison of convergence process of three algorithms.

($p_{ij} = 10$) with the other two, we can clearly see that, without distance-related definition, EE is significantly lower, especially with the increasing number of UEs. Besides, in the distance-related p_{ij} scenarios (green and red lines), with higher pass loss exponent parameter ($\alpha = 4$), EE performance (red line) obviously surpasses the one with lower $\alpha = 2$ (green line), even though, they all converge to stable EE with UE number increased. By which, we can conclude that, the definition of distance-related transaction cost p_{ij} (in (12)) can obviously improve the energy efficiency with the double auction mechanism during virtual-flow allocation period. Namely, the RA-V controller can take charge of the energy-efficiency by adjusting parameter α.

E. System Scalability and Stability

System scalability and stability are considered separately in Fig. 8 and Fig. 9, where Fig. 8 illustrates the system scalability with increasing number of InPs (BSs)[11] under different demand requirements from UEs ($r_{i,min}$). As shown in this figure, when "demand > supply" (Green line with $r_{i,min} = 10$ Mbps, red line with $r_{i,min} = 5$ Mbps and the number of InP < 5), system utility will increase when more InPs involved for offering the transmission service, which means the proposed SDV architecture encourages InPs to participate for sharing the profit during high-traffic-load period. While when "demand < supply" (Blue line with $r_{i,min} = 1$ Mbps, red line with $r_{i,min} = 5$ Mbps and number of InP > 5), system utility will decrease accordingly. This phenomenon indicates that during the low-traffic-load period, the proposed SDV architecture limits vicious competition of InPs though reducing expected profit. Besides we can clearly see that, when "demand = supply" (the black points), system utility increases with increasing number of InPs when the demand of UEs ($r_{i,min} = 1 \rightarrow 10$Mbps) rises, which in reverse

[11]We use the benchmark case parameters here, where 10 UEs and 10 InPs are considered. We assume every InP has only one BS, every BS provides $q_{j,max} = 10$ Mbps.

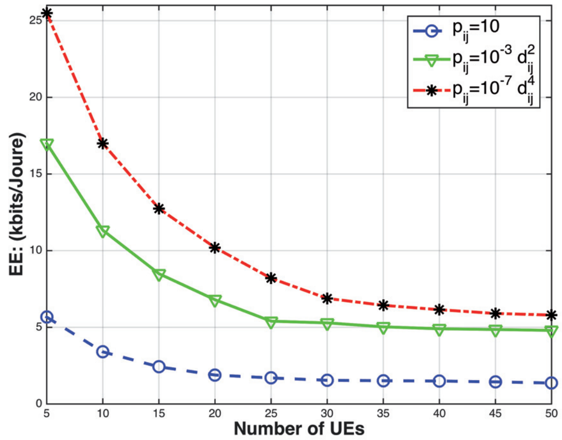


Fig. 7: Energy Efficiency (EE) with different number of UEs under devise definition of transaction cost p_{ij}.

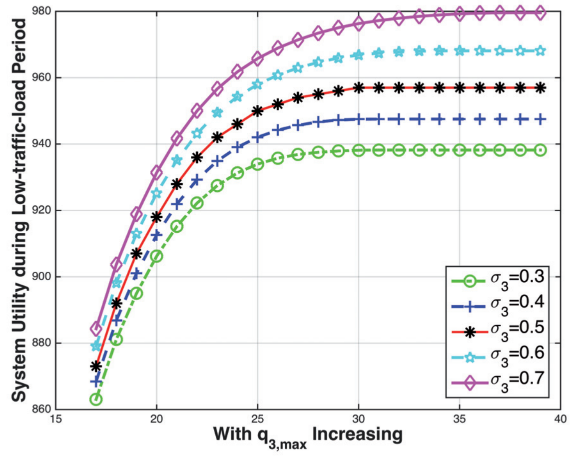


Fig. 9: System utility variety with maximum supply $q_{3,max}$ and usage-state σ_3 increasing during low-traffic-load period.

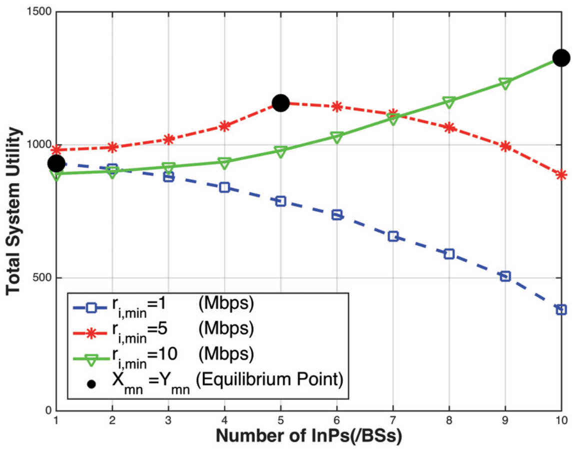


Fig. 8: System utility variety with increasing number of InPs under different QoS requirements ($r_{i,min}$).

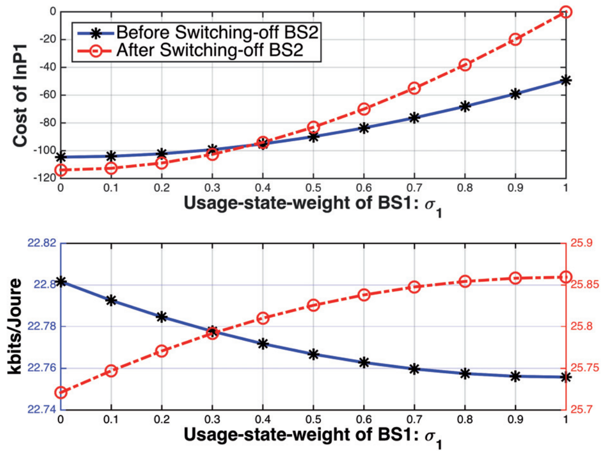


Fig. 10: The cost and EE of InP1 with BS1 usage-state-weight changing before and after switching-off BS2

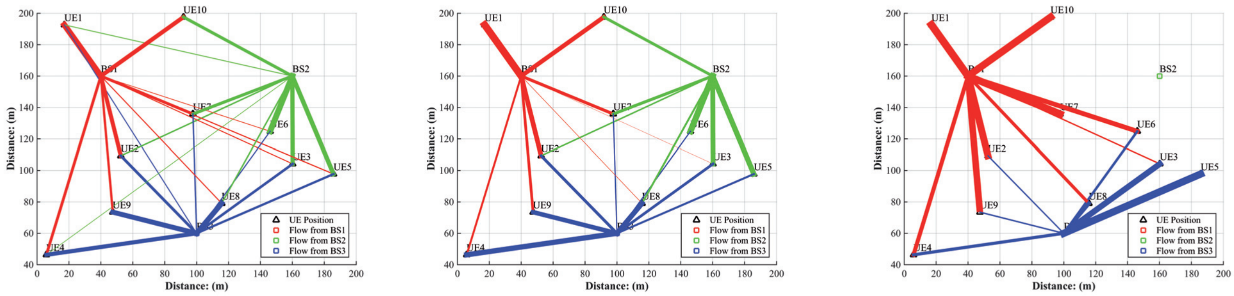
demonstrates that the proposed SDV architecture possesses the feature of scalability. In addition, Fig. 7 also shows the feature of scalability when the density of UE increases with different kinds of transaction cost.

We use Fig. 9 to illustrate the system stability with increasing supply requirements ($q_{3,max}$). This scenario is executed during low-traffic-load period and shows the system utility variety with maximum offering data rate $q_{3,max}$ and σ_3 of BS3. We can see that different BS3's usage-state ($\sigma_3 = 0.3 \rightarrow 0.7$) has a significant impact on the system utility, which is, making full use of heavy-usage-state (e.g. $\sigma_3 = 0.7$) is much more beneficial to system welfare ($\mathcal{Z}(\mathbf{x}{,}\mathbf{y})$) than using the one with light-usage-state (e.g. $\sigma_3 = 0.3$). This phenomenon shows that during low-traffic-load period, (i.e. supply $>$ demand), it is better to use BS with heavy-usage-state (larger σ), and can switch off BSs with light-usage-state for further energy consumption and OpEx reduction.

F. Swithing-off Low-traffic-load BS

Fig. 10 illustrates InP1's varying tendency of cost and energy efficiency with BS2's usage-state σ_1 when switching-off BS2. This figure shows when it is better for InP1 to make the decision for switching-off BS2 for saving energy and improving self-utility. We can clearly see that, when BS1 is in light-usage-state ($\sigma_1 \leq 0.4$), switching-off BS2 won't decrease InP1's cost. This can happen only after BS1 becomes much busier (heavy-usage-state: $\sigma_1 > 0.4$), it is because OpEx can be averaged to be lower for InPs when served with more UEs (heavier-usage-state). Moreover, Fig. 10 (the lower part) shows that with our double auction mechanism, it is always better for InP1 to switch-off BS2 with light-usage-state weight, as this can lead to lower cost and higher EE simultaneously.

In Fig. 11, we show the UE-BS association at the equilibrium. The thickness of the link indicating the amount of allocated flow (x_{ij}: from BS j to UE i). Fig. 11a and Fig. 11b illustrate how path loss exponent α affects virtual resource allocation. When α is small ($\alpha = 2$), nearly every UE needs all BSs for supporting their QoS requirements, while when α is



(a) UE-BS flow association: $\alpha = 2$, $\mathcal{Z}(\mathbf{x},\mathbf{y})$ = 957.166

(b) UE-BS flow association: $\alpha = 4$, $\mathcal{Z}(\mathbf{x},\mathbf{y})$ = 898.645

(c) Switching-off BS2, UE-BS flow association: $\alpha = 4$, $\mathcal{Z}(\mathbf{x},\mathbf{y})$ = 907.427

Fig. 11: UE-BS association and system utility at equilibrium with different pass loss exponent α setting in Case II.

larger ($\alpha = 4$), the UE-BS association changes significantly, where UEs can be satisfied through fewer BSs. Hence we can also infer that, when the interference level of the system is higher, the RA-V controller can increase the value of α for reducing the inter- or intra-tier interference. However, a small part of the system utility will be sacrificed (e.g. $\mathcal{Z}(\mathbf{x},\mathbf{y})$ decrease from 957.166 to 898.645). Fig. 11c shows the UE-BS flow-association after switching-off BS2 (as $\sigma_2 = 0.1$). We can see that even though BS1 and BS2 share the task of transmitting flow to UE1-UE10 without BS3, system utility $\mathcal{Z}(\mathbf{x},\mathbf{y})$ still has a slight increase (from 898.645 to 907.427). Hence we can conclude that, the RA-V controller can control the system association and utility by changing the distance-related transaction cost p_{ij}.

VIII. Conclusions and Future Work

In this paper, we investigated multi-flow transmission with multiple InPs and MVNOs environments. First, we introduced the architecture of SDV and virtualization process, where MVNOs can help their own subscribers to access different InPs for performance gain. Then, we formulated the virtual resource allocation problem as an optimization problem by maximizing the total utility of the system. In order to solve the problem efficiently, the virtual resource allocation problem is transformed to an iterative Double Auction problem with transaction cost. In this process, the MVNOs and InPs bid iteration by iteration according to their own utility until the system converges. The proposed I-DA mechanism satisfies the desirable economic properties and achieves higher system welfare. The simulation results show that the proposed I-DA mechanism is able to take advantage of both wireless network virtualization and multi-flow transmission. Besides, they also demonstrate the effectiveness and convergence performance of our proposed I-DA algorithm, especially in the improvement of energy efficiency when switching-off BSs during low-traffic-load period. The work in progress will consider statistical QoS requirement and caching in the proposed SDN-based virtualization architecture.

Appendix A
Proof of Theorem 2: Convergence

Differentiating the formed Lyapunov function (35) and using the chain rule, we get

$$\frac{dG(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu})}{dt} = \frac{dG}{d\lambda_i}\cdot\frac{d\lambda_i}{dt} + \frac{dG}{d\mu_j}\cdot\frac{d\mu_j}{dt} + \frac{dG}{d\nu_{ij}}\cdot\frac{d\nu_{ij}}{dt}. \quad (46)$$

According to (34), if the time-slot is small enough, we can infer that the Lagrangian multipliers are updated in the following way:

$$\frac{d\lambda_i}{dt} = \left(r_{i,min} - \sum_{j\in\mathcal{J}} x_{ij}\right)^+, \ \forall i \in \mathcal{I} \quad (47)$$

$$\frac{d\mu_j}{dt} = \left(\sum_{i\in\mathcal{I}} y_{ij} - q_{j,max}\right)^+, \ \forall j \in \mathcal{J} \quad (48)$$

$$\frac{d\nu_{ij}}{dt} = (x_{ij} - y_{ij})^+, \ \forall i \in \mathcal{I}, \forall j \in \mathcal{J}. \quad (49)$$

Then the time derivative (46) can be re-written as:

$$\begin{aligned}\frac{dG(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu})}{dt} &= \sum_{i\in\mathcal{I}} (\lambda_i - \lambda_i^*)\cdot\left(r_{i,min} - \sum_{j\in\mathcal{J}} x_{ij}\right)^+ \\ &+ \sum_{j\in\mathcal{J}} (\mu_j - \mu_j^*)\cdot\left(\sum_{i\in\mathcal{I}} y_{ij} - q_{j,max}\right)^+ \\ &+ \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} (\nu_{ij} - \nu_{ij}^*)(x_{ij} - y_{ij})^+.\end{aligned} \quad (50)$$

As $(\cdot)^+$ is the projection onto a non-negative orthant, we re-write $\frac{dG(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu})}{dt}$ as:

$$\begin{aligned}\frac{dG(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu})}{dt} &\leq \sum_{i\in\mathcal{I}} (\lambda_i - \lambda_i^*)\cdot\left(r_{i,min} - \sum_{j\in\mathcal{J}} x_{ij}\right) \\ &+ \sum_{j\in\mathcal{J}} (\mu_j - \mu_j^*)\cdot\left(\sum_{i\in\mathcal{I}} y_{ij} - q_{j,max}\right) \\ &+ \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} (\nu_{ij} - \nu_{ij}^*)(x_{ij} - y_{ij}).\end{aligned} \quad (51)$$

After adding and subtracting the optimal condition ((B3), (B4), (B5)) to the right-hand side inequality function (51), we have

$$\begin{aligned}\frac{dG(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu})}{dt} \le& \sum_{i\in\mathcal{I}} (\lambda_i - \lambda_i^*) \cdot \left(\sum_{j\in\mathcal{J}} x_{ij}^* - \sum_{j\in\mathcal{J}} x_{ij}\right)\\ &+ \sum_{i\in\mathcal{I}} (\lambda_i - \lambda_i^*) \cdot \left(r_{i,min} - \sum_{j\in\mathcal{J}} x_{ij}^*\right) \to 0\\ &+ \sum_{j\in\mathcal{J}} \left(\mu_j - \mu_j^*\right) \cdot \left(\sum_{i\in\mathcal{I}} y_{ij} - \sum_{i\in\mathcal{I}} y_{ij}^*\right)\\ &+ \sum_{j\in\mathcal{J}} \left(\mu_j - \mu_j^*\right) \cdot \left(\sum_{i\in\mathcal{I}} y_{ij}^* - q_{j,max}\right) \to 0\\ &+ \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} \left(\nu_{ij} - \nu_{ij}^*\right)\left(x_{ij} - x_{ij}^*\right)\\ &+ \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} \left(\nu_{ij} - \nu_{ij}^*\right)\left(y_{ij}^* - y_{ij}\right)\\ &+ \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} \left(\nu_{ij} - \nu_{ij}^*\right)\left(x_{ij}^* - y_{ij}^*\right) \to 0.\end{aligned} \tag{52}$$

By using (B1) and (B2) to (52), we have

$$\begin{aligned}\frac{dG(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu})}{dt} \le& \sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}} \Bigg\{ \left(x_{ij} - x_{ij}^*\right)\left(\frac{\partial \mathcal{Z}(x_{ij},\cdot)}{\partial x_{ij}} - \frac{\partial \mathcal{Z}(x_{ij}^*,\cdot)}{\partial x_{ij}}\right)\\ &- \left(y_{ij} - y_{ij}^*\right)\left(\frac{\partial \mathcal{Z}(\cdot, y_{ij})}{\partial y_{ij}} - \frac{\partial \mathcal{Z}(\cdot, y_{ij}^*)}{\partial y_{ij}}\right)\Bigg\}\end{aligned} \tag{53}$$

As function $\mathcal{Z}(\cdot)$ is strictly concave, the right-hand side of (53) is strictly non-positive. Therefore $\frac{dG(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{\nu})}{dt} \le 0$, and the equilibrium is proven to be stable at the optimal point $(\mathbf{x}^*, \mathbf{y}^*)$.

Appendix B
Proof of Lemma 1: Individual Rational

We can infer that, by satisfying Lemma 1, we need to have $\mathbf{B}_m(\mathbf{x}_m) > 0$ and $\mathbb{B}_m(\mathbf{y}_n) > 0$, i.e.

$$\begin{aligned}&\mathcal{F}_m(\mathbf{x}_m^*) > \sum_{i\in\mathcal{I}_m} \mathbf{x}_m^* \frac{\partial \mathcal{F}_i^m(\omega_i, \mathbf{x}_i^*)}{\partial \mathbf{x}_i^*},\\ &\sum_{j\in\mathcal{J}_n} \mathbf{y}_n^* \frac{\partial \Phi_j^n(\sigma_j, \mathbf{y}_j^*)}{\partial y_j^*} > \Phi_n(\mathbf{y}_n^*).\end{aligned} \tag{54}$$

As the objective functions in (29) and (31) are continuously twice differential in feasible region $\mathbb{R}^+$, we have

$$\begin{aligned}\frac{\partial \mathbf{B}_m^2(\mathbf{x}_m)}{\partial \mathbf{x}_m^2} &= \frac{\partial^2 \mathcal{F}_i^m(\omega_i, \mathbf{x}_i)}{\partial \mathbf{x}_i^2} < 0,\\ \frac{\partial \mathbb{B}_n^2(\mathbf{y}_n)}{\partial \mathbf{y}_n^2} &= -\frac{\partial^2 \Phi_j^n(\sigma_j, \mathbf{y}_j)}{\partial y_j^2} < 0.\end{aligned} \tag{55}$$

As $\mathbf{B}_m(\cdot)$ and $\mathbb{B}_n(\cdot)$ are both strictly concave, the inequality in (54) is always satisfied.

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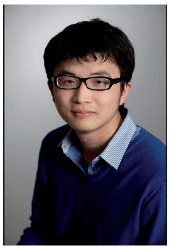

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A CONTRACT-BASED RESOURCE ALLOCATION MECHANISM IN WIRELESS VIRTUALIZED NETWORK

by

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A Contract-based Resource Allocation Mechanism in Wireless Virtualized Network

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***Abstract*—The rapidly increasing mobile traffic demand poses both new communication requirements and challenges on existing communication networks in terms of technologies and business models. Wireless network virtualization is a promising technology to provide service-based architecture and contract theory is a powerful framework from microeconomics for providing tools to model incentive mechanisms. In this work, a novel contract theoretic incentive mechanism is proposed to study how to provide services to multiple users in the wireless virtualized networks. Infrastructure providers (InPs) is considered to own the physical networks and mobile virtual network operator (MVNO) has the information of the users and needs to lease the physical radio resources for providing services to subscribed users. In particular, a contract theoretic approach is utilized to model the trading process between the MVNO and multiple InPs. Subsequently, the corresponding optimal contract is derived respectively to maximize the payoff of the MVNOs while maintaining the benefits of the InPs in the trading process. With numerical results, it can be observed that the proposed contract theoretic approach can effectively stimulate InPs' participation, improve the payoff of the MVNO and outperform other schemes.**

I. Introduction

5G communication system is forseen to provide ubiquitous connectivity for the Internet of Things (IoT) based applications. Inspired by the successful use of SDN and NFV in cloud computing, virtualization/network slicing has been introduced to mobile network for enabling flexible connectivety and cooperation to multiple InPs and MVNOs over a shared physical substate. [1]. A simple illustration of wireless virtualized network (WVN) is presented in Fig. 1. In WVN, both radio resources and physical infrastructure (from InPs'side) can be virtualized and shared, and a MVNO can rent the sliced resources in a flexible manner. Consequently, through InPs' collaborative participation, the overall capital expenses (CapEx) of deployment and operation expense (OpEx) can be reduced significantly.

Recently, there are growing research interests on enabling the network virtualization in mobile networks [2]. In particular, there are considerable efforts dedicated to the resource allocation problems in the WVN. In order to minimize the OpEx of running a physical network of an InP, the virtual resource allocation problem was formulated in a parallel and distributed way in [3], which can also ensure the minimum traffic disruption. In [4], the authors slove the radio resource slicing problem from an energy efficient way, where an OFDM-based WVN scheme together with a joint power, subcarrier, and antenna allocation scheme was proposed. The authors of [5] propose a joint virtual resource allocation and in-network caching scheme with the objective to maximize the InP's system utility by considering both the revenue earned and the cost for renting. In [6], the authors utilize contract theory to investigate the interaction between network service providers and MVNO and present a bandwidth provisioning scheme.

It can be well observed that the aforementioned resource allocation schemes mainly focus on the InP-side. That is, the works are proposed for the MVNO to decide how to slice or allocate resources to each InP to serve the users. Meanwhile, the investigation of resource allocation problems between the MVNO and InPs lacks of attention. Contract theory is viewed as efficient tool for the mathematical modelling of such an interaction [7]. The research on contract theory in wireless communications has been mainly applied to the spectrum trading problems in cognitive radio [8] [9] and incentive mechanism to promote the communication efficiency [10] [11] [12]. Therefore, utilizing contract theory to present thorough analysis of interaction of the InPs and MVNO is full of potential and can complement the current research on WNV, which, however, has not been investigated so far.

The aim of this paper is to design an incentive mechanism to maximize the overall utility of the MVNO and meanwhile enhance the InPs' satisfactions. Our contributions can be summarized as follows,

- Considering a WVN with multiple InPs and an MVNO, we propose to an incentive mechanism with contract theory to motivate InPs to offer their radio resources to provide services.
- The formulated optimization problem can be considered as an user association and power allocation problem in the wireless virtualized network, to find the user and InP association and design the transmit power allocation policy.
- The condition of feasibility and optimality has been analysed, the formulated problem can be addressed to obtain close-to-optimal solutions and simulation results evaluates the effectiveness of our scheme in the contract design and the resource allocation algorithm.

II. System Model

We consider a WVN including an MVNO and multiple InPs. MVNO owns I subscribed User Equipments (UEs), the set of

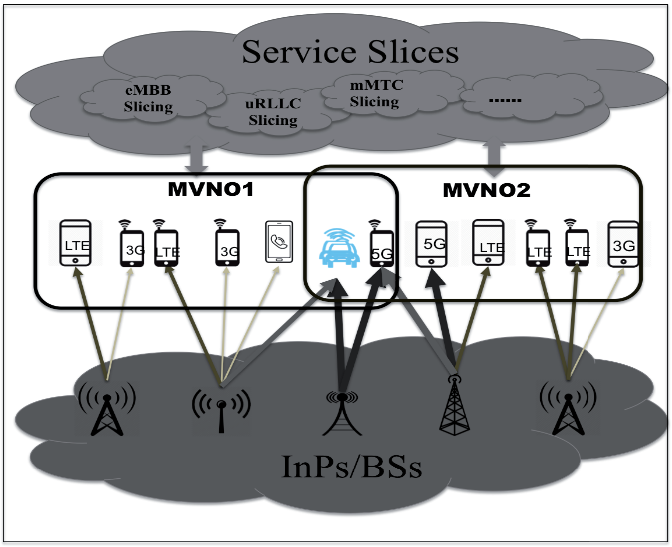

Fig. 1. The Architecture of Wireless Network Virtualization with Multiple MVNOs and InPs.

which is denoted as $\mathcal{I} = \{1, \cdots, I\}$. Each UE i ($i \in \mathcal{I}$) has specific content request s_i. In order to satisfy UEs' requests, the MVNO will offer a contract that can motivate InPs to offer the specific services effectively. There are totally J InPs, the set of which is denoted as $\mathcal{J} = \{1, \cdots, J\}$. Each InP j ($j \in \mathcal{J}$) owns a set of Base Stations (BSs): $\mathcal{N}_j = \{1, \cdots, N_j\}$ where n_j represents BS n for InP j. There are totally $K = \sum_{j\in\mathcal{J}} N_j$ BSs in the considered virtualized wireless network. We define a binary variable as follows,

$$x_{ij}^n = \begin{cases} 1, & \text{if UE } i \text{ assigned with BS } n_j, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Due to the dominating property of MVNO, the resource allocation process can be modeled as a *monopoly market*, where the MVNO will act as the employer and the InPs will act as the employees.

A. Network and Service Model

For the MVNO, it is necessary to investigate the characteristic of link between UE i and BS n_j firstly in order to offer suitable contract for InPs. We define r_{ij}^n as the data rate between UE i and BS n_j:

$$r_{ij}^n = w_{ij}^n \cdot \log_2\left(1 + p_{ij}^n \cdot \frac{|h_{ij}^n|^2}{\mathrm{I}_{i'j}^n + \mathrm{I}_{i'j'}^n + \sigma^2}\right), \tag{2}$$

where w_{ij}^n is the channel bandwidth and p_{ij}^n is the transmit power needed by UE i for the specific requested service with data size s_i with BS n_j, σ^2 is the noise variance of AWGN and $|h_{ij}^n|^2$ is the channel gain. Universal frequency reuse is considered such that an UE only receives interference from the other BSs other than its serving BS. As discussed in [2], due to the fact it is hard to coordinate the transmission among different InPs, we consider the InPs are operating on different licensed spectrum in the considered virtualized wireless network. Therefore, $\mathrm{I}_{i'j'}^n$ (interference from the BSs inside) can be furthered assumed to be neglect, and $\mathrm{I}_{i'j}^n$ (interference from the BSs outside) can be given as

$$\mathrm{I}_{i'j}^n = \sum_{n'\in\mathcal{N}_j}\sum_{i'\in\mathcal{I}\setminus i} p_{i'j}^n |h_{i'j}^n|^2, \ \forall i \in \mathcal{I}, \forall n \in \mathcal{N}_j, \tag{3}$$

where $p_{i'j}^n$ and $p_{i'j'}^n$ denote respectively the transmit power of BS n of InP j for UE i' ($i' \in \mathcal{I}\setminus i$), and the transmit power of BS n of InP j', ($j' \in \mathcal{J}\setminus j$) for UE i', $i' \in \mathcal{I}\setminus i$). $|h_{i'j}^n|^2$ and $|h_{i'j'}^n|^2$ are the corresponding channel gain.

In the following we assume $w_{ij}^n = 1$. Without loss of generality, σ^2 is also assumed to be identical for all InPs. We assume the channel is a quasi-static Rayleigh fading channel. As the channel state information is predominated to the BSs owned by the InPs, it is considered as the private information of each InP and not directly available globally or to the MVNOs. According to the difference in channel quality, the BSs was classified into different categories (types-θ):

$$\theta_{ij}^n \triangleq \frac{|h_{ij}^n|^2}{\sum\limits_{i'\in\mathcal{I}\setminus i}\sum\limits_{n'\in\mathcal{N}_j} p_{i'j}^{n'}|h_{i'j}^{n'}|^2 + \sigma^2}, \tag{4}$$

which captures all the private information of BS n_j related to its transmission link with UE i. It can be found that a larger θ_{ij}^n indicates a better channel condition and θ_{ij}^n decreases as the interference becomes strong. Moreover, the delay that UE i may experience can be expressed as,

$$D_i = \frac{s_i}{\sum\limits_{n\in\mathcal{N}_j}\sum\limits_{j\in\mathcal{J}} x_{ij}^n \cdot r_{ij}^n}, \ \forall i \in \mathcal{I}. \tag{5}$$

We denote Q_i as *service quality* for UE i, which is inversely proportional to service delay:

$$Q_i = \frac{\alpha}{D_i}, \ \alpha > 0, \ \forall i \in \mathcal{I}, \tag{6}$$

where α is the reverse function parameter, and $\alpha > 0$. We can clearly see that, less service delay (lower D_i value) leads to higher service quality (larger Q_i value).

According to the definition in (4), θ_{ij}^n information can be only measured locally by InP j. By classifying the InP type according to its BS, we can have the InP type by the following definition.

Definition 1. *For specific UE i, there are totally $K = \sum_{j\in\mathcal{J}} N_j$ BSs available for connecting, where $k \in \mathcal{K} = \{1, \cdots, K\}$. The channel quality between of BS n_j and UE i are sorted in an ascending order in Θ_i and classified into K types: type-1,$\cdots$, type-k,$\cdots$, type-K. θ_i^k is denoted as the type of BS for specific UE i and follows*

$$\theta_i^1 < \cdots < \theta_i^k < \cdots \theta_i^K, \ \forall i \in \mathcal{I}. \tag{7}$$

Specifically, we refer to InP j as a type-θ_i^k InP. A larger θ_i^k implies more willingness to contribute to the services.

Note that as $J \leq K$, one InP may be classified into different types by this definition. According to this definition, we can use BS k instead of BS n_j. Correspondingly, we can use p_i^k (p_{ij}^n), r_i^k (r_{ij}^n) and x_i^k (x_{ij}^n) instead.

B. Payoff Model of InPs

In this work, the objective of each InP is to maximize its payoff from making the contract with the MVNO and serving the UEs. The payoff of the InP consists of two parts, one is the achieved revenue from selling to MVNO and the cost for providing services to the UEs. First, we can define the cost for serving the UE i. Such a cost consists of a fixed cost (mainly BS OpEx), and a quality-related cost including the energy consumption, etc, i.e.,

$$e(x_i^k, p_i^k) = x_i^k(e_o + \Psi(p_i^k)), \tag{8}$$

where $e_o \geq 0$ is a fixed cost (e.g., maintenance cost of BS etc.) and $\Psi(p_i^k)$ is the quality-related cost.

Then, the utility/revenue of an InP by trading the service to the MVNO to serve UE i is defined as follows,

$$\pi(x_i^k, \theta_i^k, p_i^k) = \theta_i^k x_i^k \gamma R(p_i^k), \tag{9}$$

where γ is the unit cost and $R(p_i^k)$ is the payment of MVNO in the contract with the InPs. We consider the payment is related to the resource (transmit power) usage of InP and $R(x)$ is a strictly increasing concave function of x, i.e., $R(0) = 0, R'(x) > 0$ and $R''(x) < 0$ for all x. The payoff, which is the difference between the the cost and selling price can be modelled as,

$$\begin{aligned} U_k &= \sum_{i\in\mathcal{I}} \left(\pi(x_i^k, p_i^k) - e(x_i^k, p_i^k)\right) \\ &= \sum_{i\in\mathcal{I}} \sum_{k\in\mathcal{N}_j} x_i^k \left(\theta_i^k \gamma R(p_i^k) - e_o - \Psi(p_i^k)\right), \ \forall j \in \mathcal{J} \end{aligned} \tag{10}$$

As an employee, the InP will choose the contract bundle whirh can maximize its own payoff according to (10).

C. Payoff Model of MVNO

The payoff of the MVNO is defined as the difference between its revenue obtained from its served UEs and the cost paid to the InPs. First, we define *revenue* Φ_i brought by serving UE i as a linear monotonically increasing function of service quality Q_i. The more revenue UE i brought, the higher service quality needs. So the revenue function is defined as:

$$\Phi(x_i^k, p_i^k) = \beta \cdot Q_i = \alpha\beta \left(\frac{\sum_{k\in\mathcal{N}_j}\sum_{j\in\mathcal{J}} x_i^k \cdot r_i^k}{s_i}\right), \ \forall i \in \mathcal{I}, \tag{11}$$

Correspondingly, the cost of the MVNO can be considered as the utility of the InPs. Therefore, from the MVNO's perspective, we define the *payoff* brought by serving UE i, denoted by U_i, as the difference between the revenue and the cost, i.e.,

$$\begin{aligned} U_i &= \xi(x_i^k, p_i^k) - \pi(x_i^k, \theta_i^k, p_i^k) \\ &= \sum_{k\in\mathcal{N}_j} \sum_{j\in\mathcal{J}} x_i^k \left(\frac{\alpha\beta r_i^k}{s_i} - \theta_i^k \gamma R\left(p_i^k\right)\right), \ \forall i \in \mathcal{I}, \end{aligned} \tag{12}$$

To simplify the analysis, we consider $\alpha = 1$, $\beta = 1$, $s_i = 1$ and $\gamma = 1$. We can further simplify (12) as

$$U_i = \sum_{k\in\mathcal{N}_j} \sum_{j\in\mathcal{J}} x_i^k \left(\omega_i^k \log_2(1 + p_i^k \cdot \theta_i^k) - \theta_i^k R\left(p_i^k\right)\right). \tag{13}$$

By considering the heterogeneity among different InPs, the MVNO will offer different contract bundles to different InPs according to InP's type θ_i^k instead of offering the same contract. The InPs can choose to accept or decline the offering-type contract based on its own evaluation.

III. Contract Formulation and Solution

In this section, the contract offered by MVNO with asymmetric information is first formulated as $0-1$ mixed integer programming problem. Necessary definitions and lemmas are proposed and deduced in the following. Lagrangian method with elaxation and variable transformation is applied to develop the efficient algorithm.

A. Contract Formulation

In order to obtain successful service for specific UE i, the offered contract by the MVNO will highly based on the quality Q_i, which is related to p_i^k, type $\theta_i^k \in \Theta_i$, and x_i^k. Recall (5) and (6), we can rewrite the service quality as:

$$Q(x(\theta_i^k), p(\theta_i^k)) = \sum_{k\in\mathcal{K}} x_i^k \omega_i^k \log_2(1 + p_i^k \cdot \theta_i^k), \ \forall i \in \mathcal{I}. \tag{14}$$

As we can see from (10), (13) and (14), the payoff and service quality of the system depend on two factors: x_i^k and p_i^k. Therefore, we write the contract designed for the *type-*θ_i^k InP:

$$\begin{aligned} \mathbb{C} &= \{(x(\theta_i^k), p(\theta_i^k)), \ \forall \theta_i^k \in \Theta_i, \ \forall i \in \mathcal{I}\} \\ &= \{(x_i^k, p_i^k), \ \forall k \in \mathcal{K}, \ \forall i \in \mathcal{I}\}. \end{aligned} \tag{15}$$

An InP of *type-*θ_i^k selects the contract item (x_i^k, p_i^k) (i.e. user association and transmit power level) by maximizing its own payoff, i.e.,

$$(\tilde{x_i^k}, \tilde{p_i^k}) = \arg\max_{(x_i^k, p_i^k)} \pi(x_i^k, \theta_i^k, p_i^k) - e(x_i^k, p_i^k). \tag{16}$$

For a feasible contract, it must satisfy the following two constraints, which are individual rationality and incentive incentive compatibility [8].

Definition 2. *Individual Rationality (IR): The contract that an InP selects guarantee that the corresponding payoff is non-negative, i.e. InP can only accept the contract item for* θ_i^k*, i.e.,*

$$\pi_i^k - e_i^k \geq 0. \tag{17}$$

For notation simplicity, in the following, we use π_i^k to denote $\pi(x_i^k, \theta_i^k, p_i^k)$ and e_i^k to denote $e(x_i^k, p_i^k)$. Further, we denote $\upsilon_i^k = \upsilon(x_i^k, p_i^k) = x_i^k R(p_i^k)$ and $\pi_i^k = \theta_i^k \upsilon_i^k$.

Definition 3. *Incentive Compatible (IC): InPs must prefer the contract designed specifically for their own types than the others, i.e., type-θ_i^k InP prefer item (x_i^k, p_i^k) than (x_i^m, p_i^m):*

$$\pi_i^k - e_i^k \geq \pi_i^m - e_i^m, \ \forall k, m \in \mathcal{K}. \tag{18}$$

Remark: We can infer that, the IR condition ensures non-negative payoffs of InPs in the contract designed for each type so as to accept the contract with more willingness. IC constraint indicated that if type-θ_i^k-InP wants to achieve highthest utility, he can only choose the contract item designed for his own type: (x_i^k, p_i^k), because any other item will lead to payoff distortion. If a contract satisfies the IR and IC constraints, we refer to the contract as a feasible contract. Therefore, in order to maximize profit, MVNO should establish an optimal contract $(x^*(\theta_i^k), p^*(\theta_i^k))$ under feasible constraints.

We assume that the contract is under incomplete information, the optimal contract can be formulated as the MVNO's profit maximization problem:

$$\mathbf{P}: \ \max_{\{\mathbf{x}, \mathbf{p}\}} \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{K}} \mathbb{E}\{N_i^k U_i\} \tag{19}$$

$$\begin{aligned} s.t. \ \mathbf{C1}: & x_i^k = \{0,1\}, \sum_{k \in \mathcal{K}} x_i^k \leq 1, \ \forall i \in \mathcal{I}, \\ \mathbf{C2}: & 0 \leq \sum_{i \in \mathcal{I}} x_i^k p_i^k \leq p_{max}^k, \forall i \in \mathcal{I}, \ \forall k \in \mathcal{K}, \\ \mathbf{C3}: & \sum_{k \in \mathcal{K}} \rho_i^k = 1, \ \forall i \in \mathcal{I}. \\ \mathbf{C4}: & \pi_i^k - e_i^k \geq 0, \ \forall k \in \mathcal{K}, \\ \mathbf{C5}: & \pi_i^k - e_i^k \geq \pi_i^m - e_i^m, \forall k, m \in \mathcal{K}. \end{aligned} \tag{20}$$

N_i^k is assumed to be the number of type-θ_i^k-InP and $\mathbb{E}$ is its expected value. In (20), **C1** is the association constraint that one UE can be associated with at most one InP. **C2** and **C3** are the constraint of transmit power and probability. **C4** and **C5** represent the IR and IC constraints, respectively.

B. Feasibility of Contract

For each UE requirements, there are K IR constraints and $K(K-1)$ IC constraints in (20), which are non-convex and coupled among different InPs, which hard to solve directly. Motivated by [10], this optimal contract design can be defined as adverse selection problem, which can be solved step-by-step. Firstly, IR and IC constraints can be reduced by following lemmas.

Lemma 1. *If the payoff of the MVNO is maximized under asymmetric information scenario, i.e., the optimal contract design is obtained, IR constraint can be replaced by:*

$$\widetilde{\boldsymbol{C4}}: \pi_i^1 - e_i^1 = 0, \ \forall k \in \mathcal{K}. \tag{21}$$

given the IC constraints are satisfied.

Proof. Firstly, for any feasible contract $\mathbb{C}$, $\upsilon_i^k > \upsilon_i^m$ *if* $\theta_i^k > \theta_i^m$, and $\upsilon_i^k = \upsilon_i^m$ *if* $\theta_i^k = \theta_i^m$. Deduced from Definition 1, user type satisfies $\theta_i^1 < \cdots < \theta_i^k < \cdots \theta_i^K$, plus IC constraints, we can see:

$$\begin{aligned} \theta_i^k \upsilon_i^k - e_i^k > \theta_i^m \upsilon_i^m - e_i^m, \\ \theta_i^m \upsilon_i^m - e_i^m > \theta_i^m \upsilon_i^k - e_i^k. \end{aligned} \tag{22}$$

Then we deduce that

$$\theta_i^k \upsilon_i^k - e_i^k \geq \theta_i^k \upsilon_i^m - e_i^m \geq \theta_i^m \upsilon_i^m - e_i^m, \tag{23}$$

where if the first type-BS IR constraint is guranteed, the other IR constraints for all othe BS types will automatically hold, i.e. when $m = 1$:

$$\theta_i^1 \upsilon_i^1 - e_i^1 \geq 0. \tag{24}$$

Finally, from **C1**, we can see that for any UE i, there can be only one contract that $x_i^k = 1$ and the others should equal to zero. Therefore, for any feasible contract $\mathbb{C}$, only one contract item of the highest type θ_i^K can have positive user association and all other items should have zero association, i.e.,

$$\begin{cases} x_i^k \leq 1, & \text{if } k = K, \\ x_i^k = 0, & \text{otherwise.} \end{cases} \tag{25}$$

Thus, we rewrite (24) and complete the proof

$$\theta_i^1 \upsilon_i^1 (= \pi_i^1) - e_i^1 = 0. \tag{26}$$

□

Remark: From Lemma 1, we can infer that if $\theta_i^k > \theta_i^m$ holds, then $\upsilon_i^k > \upsilon_i^m$ must hold. Thus, a InP with a higher type will obtain more reward than a InP with lower type. In situation where two InPs receive the same profit, they two must be included in the same type and vice versa. Considering the **Definition 1**, we can have $\upsilon_i^1 < ... < \upsilon_i^k < \upsilon_i^K)$ and $0 \leq e_i^1 < ... < e_i^k < ... < e_i^K$. Correspondingly, we can have the following definition.

Definition 4. *Monotonicity: If* $\theta_i^k \geq \theta_i^m$, $\forall k, m \in \{1, \cdots, K\}$ *and then* $\pi_i^k \geq \pi_i^m$.

This definition indicates that efficient type results in more profit, even at the margin utility. Obviously type-θ_i^k InPs utility function (10) satisfies the *Monotonicity*. According to [11], we can further deduce:

Lemma 2. *With Monotonicity, the IC condition can be reduced as the local downward incentive compatibility (LDIC), given by:*

$$\pi_i^k - e_i^k \geq \pi_i^{k-1} - e_i^{k-1}. \tag{27}$$

and the local upward incentive compatibility (LUIC), given by

$$\pi_i^k - e_i^k \geq \pi_i^{k+1} - e_i^{k+1}. \tag{28}$$

Proof. Firstly, we proof the LDIC. Consider three types of InPs $\theta_i^{k-1} < \theta_i^k < \theta_i^{k+1}$, and we obtain

$$\begin{aligned} &\pi(x_i^{k+1}, \theta_i^{k+1}, p_i^{k+1}) - e(x_i^{k+1}, p_i^{k+1}) \geq \\ &\pi(x_i^k, \theta_i^{k+1}, p_i^k) - e(x_i^k, p_i^k), \end{aligned} \tag{29}$$

and

$$\begin{aligned} &\pi(x_i^k, \theta_i^k, p_i^k) - e(x_i^k, p_i^k) \geq \\ &\pi(x_i^{k-1}, \theta_i^k, p_i^{k-1}) - e(x_i^{k-1}, p_i^{k-1}). \end{aligned} \tag{30}$$

In **Lemma 1**, we can see that $\upsilon_i^k \geq \upsilon_i^m$ whenever $\theta_i^k \geq \theta_i^m$, then (29) and (30) becomes

$$\theta_i^{k+1}(\upsilon_i^k - \upsilon_i^{k-1}) \geq \theta_i^k(\upsilon_i^k - \upsilon_i^{k-1}) \geq e_i^k - e_i^{k-1}, \tag{31}$$

$$\theta_i^{k+1}\upsilon_i^{k+1} - e_i^{k+1} \geq \theta_i^{k+1}\upsilon_i^k - e_i^k \geq \theta_i^{k+1}\upsilon_i^{k-1} - e_i^{k-1}, \tag{32}$$

which implies that for InP type θ_i^{k+1}, besides (x_i^k, p_i^k), the LDIC is satisfied for contract item (x_i^{k-1}, p_i^{k-1}). By iterating, it can be deduced the LDIC holds for all contract items (x_i^m, p_i^m) when $m \leq k$, i.e. LDIC constraint is satisfied.

Secondly, as the LUIC proof is similar to the LDIC proof, we omit it here for space constraint. As θ_i^{k+1} is randomly selected, the proof completes in perspective of randomness. □

Remark: Based on the above lemmas and proof, the IC constraints can be simplified and replaced by the LDICs and LUICs. Similar with Lemma 1, we further reduce **C5** by analysising LDICs in more detail. The LUICs are similar to the LDICs.

Lemma 3. *The LDICs must satisfy the following condition if the payoff of the MVNO is maximized,*

$$\begin{aligned} &\pi(x_i^k, \theta_i^k, p_i^k) - e(x_i^k, p_i^k) = \\ &\pi(x_i^{k-1}, \theta_i^k, p_i^{k-1}) - e(x_i^{k-1}, p_i^{k-1}). \end{aligned} \tag{33}$$

i.e. ***C5*** *can be reduced as*

$$\widetilde{\textbf{\textit{C5.1}}}: \theta_i^k \upsilon_i^k - e_i^k = \theta_i^k \upsilon_i^{k-1} - e_i^{k-1}, \forall k \in \mathcal{K}. \tag{34}$$

and

$$\widetilde{\textbf{\textit{C5.2}}}: 0 \leq U_i^1 < ... < U_i^k < ... < U_i^K. \tag{35}$$

Proof. Suppose the LDICs hold for any type of InP θ_i^k. The LDICs will still be satisfied if both $e(x_i^k, p_i^k)$ and $e(x_i^{k-1}, p_i^{k-1})$ are raised by the same positive amount. To maximize its payoff, the MVNO will try to raise the use of radio resources for as much as possible until the following equation satisfies, i.e., $\pi(x_i^k, \theta_i^k, p_i^k) - e(x_i^k, p_i^k) = \pi(x_i^{k-1}, \theta_i^k, p_i^{k-1}) - e(x_i^{k-1}, p_i^{k-1})$. Note that this process will not impact on other LDIC conditions. Therefore, if the contract is achieved the optimum, the LDIC conditions will hold. □

Remark: Similarly, we can conclude that all the LUICs will hold by considering both the LDIC-conditions and the *monotonicity* condition. That is, $\pi(x_i^k, \theta_i^k, p_i^k) - e(x_i^k, p_i^k) = \pi(x_i^{k-1}, \theta_i^k, p_i^{k-1}) - e(x_i^{k-1}, p_i^{k-1})$ implies that $\pi(x_i^k, \theta_i^k, p_i^k) - e(x_i^k, p_i^k) \geq \pi(x_i^{k-1}, \theta_i^k, p_i^{k-1}) - e(x_i^{k-1}, p_i^{k-1})$. Therefore, with LDICs and the *monotonicity* condition, IC constraint can be reduced obviously.

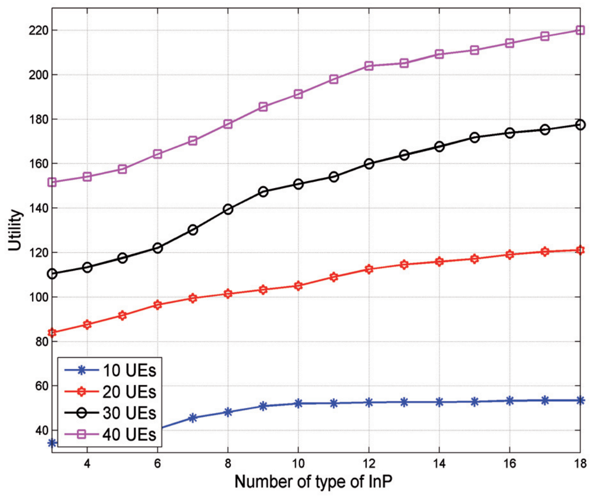

Fig. 2. MVNO's utility with respect to number of UEs and InP types.

C. Optimality of Contract

In this case, the MVNO does not know the exact type of each InP, but the number of InPs (N) and the probability distribution of InP type are assumed to be known. Such a probablity can be denoted as $\rho_i^k = \Pr\{\theta_i^k = \theta_{ij}^n\}$, $\forall n \in \mathcal{N}_j$, $\forall j \in \mathcal{J}$. Obviously, $\sum_{k \in \mathcal{K}} \rho_i^k = 1$, $\forall i \in \mathcal{I}$. Consequently, to find a feasible and optimal solution, (19) can be reformed as:

$$\begin{aligned} \widetilde{\mathbf{P}}: \ &\max_{\{\mathbf{x},\mathbf{p}\}} \sum_{i \in \mathcal{I}} \sum_{k \in \mathcal{K}} \rho_i^k N U_i \\ s.t. \ &\mathbf{C1}, \ \mathbf{C2}, \ \mathbf{C3}, \\ &\widetilde{\mathbf{C4}}, \ \widetilde{\mathbf{C5.1}}, \ \widetilde{\mathbf{C5.2}}. \end{aligned} \tag{36}$$

Note that $\widetilde{\mathbf{P}}$ becomes a concave problem. So we can leverage standard convex optimization tools in [12] to solve it to get p_i^k, and then x_i^k can be calculated iteratively by the first two constraints in (36). Moreover, monotonicity is met automatically when the type is uniformly distributed. So far, we have derived the optimal contract (x_i^k, p_i^k), $\forall i \in \mathcal{I}$, $\forall k \in \mathcal{K}$, which can maximize the utility of the MVNO and satisfy the constraints of IR and IC.

IV. Performance Evaluation

In this section, numerical simulations is conducted to validate the feasibility and performance of our mechanism and guide MVNO to propose optimal contract for InPs. For simplicity, we assume there are three InPs and they are operating in a $100 \times 100 m^2$ area, and there are 20 UEs in this area requesting the mobile service from the MVNO. It is considered that the UEs are randomly located. The maximum transmit power of the BS of the InP is 46 dBm unless specified. Further, we define the quality-related cost $\Psi(p_i^k)$ in (8) as a linear cost related to the power consumption, i.e., $\Psi(p_i^k) = \tau p_i^k$, where τ is the cost parameter. Therefore, $\Psi(p_i^k)$ increments

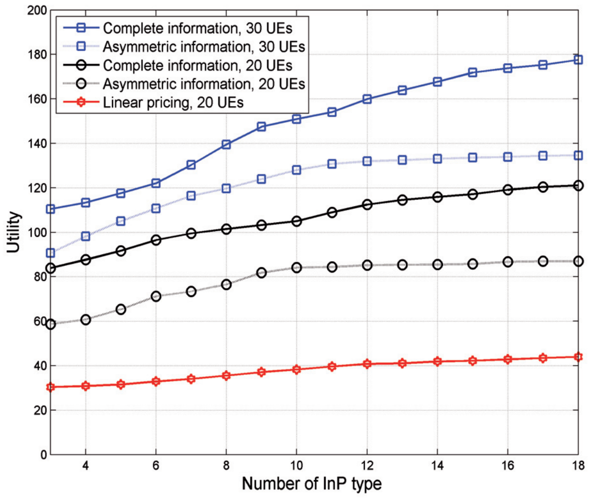

Fig. 3. MVNO's utility with respect to InP types, complete information case v.s. asymmetric information case v.s. linear pricing case, 10 and 30 UEs.

linearly with the cost of power consumption, and without being specified, we consider $\tau = 1$ and $R(x) = clog(x)$ in (9), where c is a constant.

In Fig. 2, we present the MVNO's utility with respect to number of UEs and InP types. First, we can observe that as the number of types of InPs increases, the overall utility also gets larger. This is mainly due to the fact that the increase of the number of types of InPs essentially mean there are more and better options to provide better services to the UEs. Therefore, the utility, which is related to the data rate of the UEs, increases as well. However, when there are only 10 UEs in the system, the increment of the utility becomes slow when the number of types of InPs is above 10. This may due to the fact that in this area, there are enough number of types of InPs for the UEs. Simply increasing the types of InPs will not improve the service quality, as the BSs of the InPs may be close enough to the UEs. When there are 20 UEs, the utility can be improved as the number of types of InPs without any saturation. However, the speed of increment becomes slow. For the cases with 30 and 40 UEs, the utility always increases when there are more types of InPs, which means there are still room for the service provisioning of the MVNO.

In Fig. 3, we have compared the utility performance of our contract with the one under complete information[1]. We also show a linear pricing mechanism here [10] with information asymmetry, where the offered price by MVNO is linear to the transmit power. It can be found in Fig.3 that the MVNO achieves the highest utility when the types of the InPs are known, i.e. symmetric/complete information. For the case with asymmetric information, as the real value of InP type is unavailable to the MVNO, the MVNO can only approach the near-optimal result, which is upper bounded by the complete information case. Meanwhile, the proposed solution for the contract yields an better utility compared with the linear pricing case. As in the linear pricing case, the choices of the InPs are flexible and unpredictable, which prevents the MVNO to offer suitable contracts and obtain more utility.

[1]In a complete information scenario, the MVNO is assumed to know precisely the type of the InPs, so as the BSs [11].

V. Conclusions

A contract-based incentive mechanism for the network virtualization with multiple InPs in 5G-radio access network was developed. By providing compatible incentive to the InPs under information asymmetry, the corresponding optimal contract is derived to maximize the payoff of the MVNO while maintaining the requirements of the UEs in the trading process. Moreover, extensive simulation studies are conducted and can be observed that the contract theoretic approach can effectively stimulate InPs' participation, improve the payoff of the MVNO and outperform other schemes significantlly. The future work will consider different QoS requirements and caching of the proposed contract-based incentive mechanism at the context of this 5G virtualization architecture.

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INCENTIVE MECHANISM FOR RESOURCE ALLOCATION IN WIRELESS VIRTUALIZED NETWORKS WITH MULTIPLE INFRASTRUCTURE PROVIDERS

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