An Integrated Spectrum and Information Market for Green Cognitive Communications

Yuan Luo, Lin Gao, *Member, IEEE*, and Jianwei Huang, *Fellow, IEEE*

***Abstract*— A database-assisted TV white space network can achieve the goal of green cognitive communication by effectively reducing the energy consumption in cognitive communications. The success of such a novel network relies on a proper business model that provides substantial incentives for all parties involved. In this paper, we propose an integrated spectrum and information market for a database-assisted TV white space network, where a geolocation database acts as an online platform providing services to both a spectrum market and an information market. We model the interactions among the database operator, the spectrum licensee, and the unlicensed users as a three-stage sequential decision process. Specifically, Stage I characterizes the negotiation between the database and the spectrum licensee, in terms of the commission for the licensee to use the spectrum market platform, Stage II models the pricing decisions of the database and the spectrum licensee, and Stage III characterizes the subscription behaviors of the unlicensed users. Analyzing such a three-stage model is very challenging due to the co-existence of positive and negative network externalities in the information market. We explicitly characterize the impact of network externalities on the equilibrium behaviors of all parties involved. We also analytically show that the spectrum licensee can never get a market share larger than half in the integrated market. Our numerical results further show that the proposed integrated market can outperform the pure information market in terms of network profit up to 87%.**

***Index Terms*— TV white space, information market, spectrum trading market, game theory.**

I. Introduction

A. Background

WITH the explosive growth of smartphones and bandwidth-hungry wireless applications, the corresponding energy consumption due to telecommunication industry is increasing at a unprecedented speed of $16\% - 20\%$ per annum [1]. Moreover, according to the Climate Group SMART 2020 Report [2], the information and communication technology (ICT) infrastructures account for 3% of global energy consumption and 2% of global CO_2 emissions. Hence, energy optimization of wireless communications, ranging from equipment manufacturing to core functionalities, becomes increasingly important for protecting our environment, coping with global warming, and facilitating sustainable development.

Cognitive communication has been viewed as a promising paradigm for achieving energy-efficient communications. The key idea is to allow the cognitive radio device to *adapt* its configuration and transmission decision to the real-time radio environment. Hence, a cognitive radio device can select the best reconfiguration operation that balances the energy consumption and communication quality. Obviously, the success of cognitive communication system greatly relies on the accurate detection of radio environment (*e.g.,* locating the idle channels and figuring out the maximum allowable transmission power that will not bring harmful interference to the existing licensed users). If a mobile device is fully responsible for the continuous and accurate detection of radio environment, it would consume a significant amount of energy. The higher accuracy, the higher computational burden on a mobile device, and thus the higher energy consumption.

In order to reduce energy consumption and guarantee the performance of cognitive communication, some spectrum regulators (such as FCC in the USA and Ofcom in the UK), together with standards bodies and industrial organizations have advocated a *database-assisted* TV white space network architecture [3], [4]. In such a network, a white space database (called geo-location database) assists unlicensed wireless devices (called white space devices, WSDs) opportunistically exploit the under-utilized UHF/VHF frequency band, which is originally assigned for broadcast television services (hereafter called TV channels). The main reason for choosing the UHF/VHF frequency band to support cognitive communications is two-fold. First, this band is largely under-utilized by the TV broadcast services. Second, this low-frequency band can support long-distance wireless communications with low transmission power (hence low energy consumption), comparing with the current spectrum bands used by cellular networks and WiFi networks.

In such a database-assisted network, the database houses a global repository of TV licensees, and updates the licensees' channel occupations periodically. Each WSD obtains the available TV channel information via querying a geo-location database (via some existing communication networks such as cellular or Wi-Fi networks), rather than having to directly sense the TV channels which lead to significant energy consumption. Hence, WSDs are mainly responsible for performing the necessary local computations (*e.g.,* identifying

Manuscript received August 1, 2015; revised January 1, 2016 and March 17, 2016; accepted June 28, 2016. Date of publication August 12, 2016; date of current version December 29, 2016. This work was supported by the General Research Funds through the University Grant Committee of the Hong Kong Special Administrative Region, China under Project CUHK 14202814. *(Corresponding author: Jianwei Huang.)*

Y. Luo and J. Huang are with the Network Communications and Economics Laboratory, Department of Information Engineering, The Chinese University of Hong Kong, Hong Kong (e-mail: yluo@ie.cuhk.edu.hk; jwhuang@ie.cuhk.edu.hk).

L. Gao is with the School of Electronic and Information Engineering, Harbin Institute of Technology (Shenzhen), Xili, Shenzhen, China 518055 (e-mail: gaolin@hitsz.edu.cn).

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

Digital Object Identifier 10.1109/JSAC.2016.2600118

their locations), and databases are responsible for performing intensive data processing (*e.g.,* computing the available TV channels for each WSD based on the channel availabilities and the WSD location). Such a network architecture can effectively reduce the overall energy consumptions and lead to a green communication ecosystem.

According to existing related regulations, the geo-location databases are operated by third-party companies (instead of directly by the regulators or TV license owners). These database operators such as SpectrumBridge, Microsoft, and Google need to cover its capital expense (CapEx) and operating expense (OpEx) through a properly designed business model. Existing models related to the database-assisted network can be categorized into two classes: *Spectrum Market* [5], [6] and *Information Market* [7], [8].

Spectrum market has been widely used in conventional cognitive radio networks for modeling the secondary spectrum trading [16]–[18]. In database-assisted TV white space networks, the spectrum market was mainly designed the trading of licensed TV channels, i.e., those registered to some TV licensees already but are under-utilized by the corresponding licensees [5], [6]. Hence, the licensees can temporarily lease the under-utilized (licensed) TV channels to WSDs which are able to enjoy an exclusive usage right during a short time period. This will generate some additional revenue for the licensees. The database serves as a market platform facilitating such a spectrum market.[1] Spectrum Bridge, the world first certified geo-location database, provides such a *database-provided* spectrum market platform called *SpecEx*.

The information market was mainly designed for the unlicensed TV channels (*i.e.,* TV white spaces) in our early work [7], [8]. The unlicensed TV channels are those *not* registered to any TV licensee at a particular location (for example, outside the official coverage range of the TV towers), hence are the *public resources* at that location. The spectrum regulators can assign the unlicensed TV channels for the public and shared usage among unlicensed WSDs, and usually do not allow direct trading of such channels in a spectrum market. As these channels will be used by WSDs in a shared manner (in contrast to the exclusive usage in the spectrum market), the communication quality in these unlicensed TV channels is usually not guaranteed. Notice that the database knows more advanced information regarding the quality of unlicensed TV channels than unlicensed users.[2] Hence, it can sell this information to the unlicensed users through an information market, which not only improves the unlicensed users' expected communication quality, but also provides additional profit to the database. A commercial example of information market is *White Space Plus*, again operated by Spectrum Bridge.

The above works [5]–[8] studied the spectrum market and information market separately and independently. In practice, however, *the licensed TV channels and unlicensed TV channels often co-exist at a particular location* [9]. Some users may prefer to lease the licensed TV channels for the exclusive usage, while other users may prefer to share the free unlicensed TV channels with others (and purchase advanced information if needed). Hence, a joint formulation and optimization of both spectrum market and information market is important for the practical large scale deployment of the database-based TV white space network. However, none of the existing works [5]–[8] on economics of TV white space networks looked at the interaction between spectrum market and information market. This motivates our study of an *integrated* spectrum and information market for such a database-assisted TV white space network.

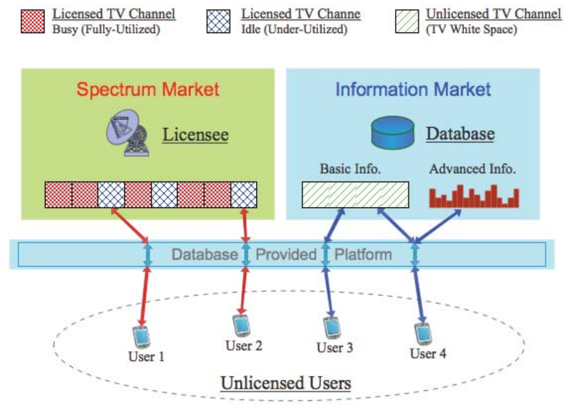


Fig. 1. Illustration of database-provided integrated spectrum and information market. Users 1 and 2 lease the licensed TV channels from the spectrum market, and users 3 and 4 share the free unlicensed TV channels with others. User 4 further purchases the advanced information from the information market to improve its performance.

B. Contributions

In this paper, we model and study an integrated spectrum and information market for a database-assisted TV white space network, in which the geo-location database serves as (i) a *spectrum market* platform for the trading of (under-utilized) licensed TV channels between spectrum licensees and unlicensed users,[3] and (ii) an *information market* platform for the trading of information (regarding the unlicensed TV channels) between the database itself and unlicensed users. Unlicensed users can choose to lease the licensed TV channels from licensees (via the database) for the exclusive usage, or to share the free unlicensed TV channels with others and purchase the advanced information from the information market if needed. Figure 1 illustrates such an integrated market.

To understand the market dynamics and equilibrium behaviors in such an integrated market, we formulate the interactions among the database (operator), the spectrum licensee, and unlicensed users as a three-stage hierarchical model:

1) Stage I—Commission Negotiation (Section VI): In Stage I, the database and the spectrum licensee negotiate regarding the commission for the licensee to use the spectrum market platform. Specifically, the database provides a platform facilitating the under-utilized licensed TV channels trading

[1] For example, it can act as a spectrum broker or agent, purchase spectrum from licensees and then resell the purchased spectrum to unlicensed users.

[2] For example, based on the knowledge about the network infrastructures of TV licensees and their licensed channels, the database can predict the average interference (from licensed devices) on each TV channel at each location.

[3] For convenience, we will call "white space devices" as "unlicensed users" in this paper.

between the licensee and unlicensed users. In return, the database takes some *commission charge* from each successful transaction between the spectrum licensee and unlicensed users. We consider two different commission charging schemes: (i) *revenue sharing* scheme (RSS), where the licensee shares a fixed percentage of revenue with the database, and (ii) *wholesale pricing* scheme (WPS), where the database charges a fixed wholesale price from each successful transaction of the licensee. We assume that both the database and spectrum licensee have market powers, and study the equilibrium commission charge decisions under both schemes using the Nash bargaining theory [10].

2) Stage II—Price Competition Game (Section V): In Stage II, the database and the spectrum licensee compete with each other for selling information or channels to unlicensed users. The spectrum licensee decides the price of the licensed TV channels, and the database decides the price of the advanced information (regarding the unlicensed TV channels). We analyze such a price competition game, and show that it is a supermodular game [11] with nice properties.

3) Stage III—User Behavior and Market Dynamics (Section IV): In Stage III, unlicensed users decide the best subscription decisions, given the database's information price and the licensee's spectrum price. Note that the users need to consider both *negative network externality* (due to congestion and interference) and *positive network externality* (due to the quality of information provided by the database) of the information market. We will show how the market dynamically evolves based on users' choices.

We summarize the main contributions as follows.

- *Novelty and Practical Significance:* We propose and study the first integrated spectrum and information market in the literature, for promoting the unlicensed spectrum access to both licensed and unlicensed TV channels. The proposed model captures both the positive and negative network externaltiy of the TV white space network.
- *Market Equilibrium Analysis:* We characterize the sufficient condition under which the proposed integrated market has a unique (user subscription) market equilibrium. We prove that the unique equilibrium is stable, in the sense that a small fluctuation on the equilibrium will drive the market back to the equilibrium.
- *Price Competition Analysis:* We study the price competition between the database and the licensee and prove the existence and uniqueness of the price equilibrium. Key contributions of our analysis involves the transformation of the price competition game into an equivalent market share competition game, and demonstrate the existence and uniqueness of the equilibrium using supermodular game theory.
- *Commission Charge Bargaining Analysis:* We adopt the Nash bargaining framework to achieve a fair and Pareto-efficient commission charge between the database and the licensee, under both revenue sharing scheme (RSS) and wholesale pricing scheme (WPS).
- *Observations and Insights:* We show that in this integrated spectrum and information market, the market share equilibrium of the licensee is always no more than half. In terms of the network profit, our proposed integrated market scheme can improve up to 87% comparing with a pure information market, and the gap with the coordinated benchmark is less than 10%. When further comparing our two proposed commission charging schemes, we show that when the negative network externality is dominant, RSS is a better choice for the database, while WPS is a better choice fort the licensee. When the positive network externality is dominant, WPS is a better choice for both the database and the licensee.

The rest of the paper is organized as follows. In Section II, we review the related literature. In Section III, we present the system model. In Sections IV-VI, we analyze the market equilibrium in Stage III, the price competition game game in Stage II, and the commission bargaining solution in Stage I, respectively. In Section VII, we provide the simulation results. Finally, we conclude in Section VIII.

II. Related Work

Most of the existing studies on green cognitive communications aimed at addressing the technical issues. For example, Hafeez and Elmirghani in [13] presented a new licensed shared access spectrum sharing scheme to increase the energy efficiency in a network. Palicot in [14] demonstrated how to achieve green radio communications by employing cognitive radio technology. Ji *et al.* in [15] proposed a platform to explore TV white space in order to achieve green communications in cognitive radio network. Successful commercialization of new green cognitive technology, however, not only relies on sound engineering, but also depends on the proper design of a business model that provides sufficient incentives to the involved parties such as the network operators. The joint study of technology and business issues is relatively under explored in the current green cognitive radio literature.

A common approach for studying market price competition is to model and analyze it as a non-cooperative game. For example, Niyato and Hossain in [16] proposed an iterative algorithm to achieve the Nash equilibrium in the competitive spectrum trading market. Gao *et al.* proposed a contract-theoretical approach in [17] and an integrated auction and contract design [18] for the monopoly spectrum trading market. Min *et al.* in [19] studied two wireless service providers' pricing competition by considering spectrum heterogeneity. Zhu *et al.* in [20] studied pricing competition among macrocell service providers via a two-stage multi-leader-follow game. In the above literature, the market is assumed to be associated with the negative network externality or non-externality. Luo *et al.* in [8] studied the price competition in the information market of TV white space, where the information market is only associated with the positive network externality. In our work, the integrated market is associated with both the positive and negative network externality. Our numerical results show that the database benefits from the positive network externality, while the licensee benefits from the negative network externality. Furthermore, which commission charging scheme is better for the database or the licensee depends on what kind of network externality is dominant in the network. This makes our market analysis quite different with the above works.

III. System Model

We consider a database-assisted TV white space network, with a *geo-location database* (or *database* for short) and a set of *unlicensed users* (or *users* for short). There exist some unlicensed TV channels, which can be used by unlicensed users freely in a shared manner (*e.g.,* using CDMA). Meanwhile, there is a *spectrum licensee*, who owns some licensed channels and wants to lease the under-utilized channels to users for additional revenue.[4] Different from the unlicensed TV channels, the licensed TV channels can be used by users in an exclusive manner (with the permission of the licensee). Therefore, users can enjoy a better performance (*e.g.,* a higher data rate or a lower interference) on the licensed TV channels.

A. Services Offered by the Database

Motivated by the current regulatory practices and commercial examples, we assume that the database provides the following three services to the users.

1) Basic Service: Regulators such as Ofcom in the UK and FCC in the US require a database to provide an unlicensed user with the following information [3], [4]: (i) the list of unlicensed TV channels, and (ii) each channel's transmission constraints such as the maximum allowable transmission power. This *basic (information) service* is free of charge.

2) Advanced Service: Beyond the basic information, the database can also provide certain advanced information regarding the quality of TV channels (as SpectrumBridge did in White Space Plus), as long as it does not conflict with the free basic service. We refer to such additional service as the *advanced (information) service*. A typical example of such an advanced information is "the interference level on each channel", which will be shown in [36]. With the advanced information, the user is able to choose a channel with the highest quality (*e.g.,* with the lowest interference level). Hence, the database can *sell* this advanced information to users for profit. This leads to an *information market*.

3) Leasing Service: As mentioned previously, the database can also serve as a spectrum market *platform* for the trading of licensed channels between the spectrum licensee and users, which we call the *leasing service* (as SpectrumBridge did in SpecEx). In return, the database will charge commission to the spectrum licensee when a trading happens. Through using the database as the trading platform, the licensees received the *aggregation benefit* [21], comparing with the case that they try to directly reach leasing agreement with users. We consider two different commission charging schemes: (i) *revenue sharing* scheme (RSS), where the licensee shares a fixed percentage of revenue with the database, and (ii) *wholesale pricing* scheme (WPS), where the database charges a fixed wholesale price from each successful transaction, regardless of the licensee's revenue from that transaction.[5]

B. A User's Choices

Users can choose either to purchase the licensed channel from the licensee for the exclusive usage, or to share the unlicensed TV channels with others (with and without advanced information). We assume that all licensed and unlicensed TV channels have the same bandwidth (*e.g.,* 8MHz in UK), and each user only needs one channel (either licensed or unlicensed) at a particular time.

We denote $s \in \{\mathsf{b}, \mathsf{a}, \mathsf{l}\}$ as the *strategy* of a user, where

(i) $s = \mathsf{b}$: Choose the basic service (*i.e.,* share unlicensed channels with others, without the advanced information);

(ii) $s = \mathsf{a}$: Choose the advanced service (*i.e.,* share unlicensed channels with others, with the advanced information).

(iii) $s = \mathsf{l}$: Choose the leasing service (*i.e.,* lease the licensed channel for the exclusive usage).

We further denote $B(\eta_{\rm L})$, $A(\eta_{\rm A}, \eta_{\rm L})$, and L as the expected *utilities* that a user can achieve from choosing the basic service ($s = \mathsf{b}$), the advanced service ($s = \mathsf{a}$), and the leasing service ($s = \mathsf{l}$), respectively. Here, $\eta_{\rm B}$, $\eta_{\rm A}$, and $\eta_{\rm L}$ is the *market shares* of the basic service, the advanced service, and the leasing service, respectively. Obviously, $\eta_{\rm B}, \eta_{\rm A}, \eta_{\rm L} \geq 0$ and $\eta_{\rm B} + \eta_{\rm A} + \eta_{\rm L} = 1$. As explained in Section III-C, the values of $B(\eta_{\rm L})$ and $A(\eta_{\rm A}, \eta_{\rm L})$ depend on all users' choices, while the value of L is independent of market share. The *payoff* of a user is defined as the difference between the achieved utility and the cost (*i.e.,* the information price when choosing the advanced service, or the leasing price if choosing the leasing service). Let θ denote the user's evaluation for the achieved utility,[6] $\pi_{\rm L} \geq 0$ denote the leasing price of the licensee, and $\pi_{\rm A} \geq 0$ denote the (advanced) information price of the database. Then, the payoff of a user with an evaluation factor θ is

$$\Pi_\theta^{\rm EU} = \begin{cases} \theta \cdot B(\eta_{\rm L}), & \text{if } s = \mathsf{b}, \\ \theta \cdot A(\eta_{\rm A}, \eta_{\rm L}) - \pi_{\rm A}, & \text{if } s = \mathsf{a}, \\ \theta \cdot L - \pi_{\rm L}, & \text{if } s = \mathsf{l}. \end{cases} \qquad (1)$$

A rational user will choose a strategy $s \in \{\mathsf{b}, \mathsf{a}, \mathsf{l}\}$ to maximize its payoff. Note that users are heterogeneous in terms of θ, which characterizes how different users evaluate the same data rate.

Let $c_{\rm A}$ denote the energy consumption cost of the database for providing the advance service, and let $c_{\rm L}$ denote the energy consumption cost of the licensee for providing the leasing service. For the rest of the paper, we will also use "operational cost" to refer to these costs.

We further denote $\delta \in [0, 1]$ as the revenue sharing percentage under RSS, and $w \geq 0$ as the wholesale price under WPS. We assume a unit population of agents., (*i.e.,* the total number of users is equal to 1). Then, the *payoffs* (profits)

[4]In case there are multiple spectrum licensees, we assume that they are coordinated by the single representative. We will study the more general issue of licensee competition in the future work.

[5]Both commission charging schemes are widely used in practice. The revenue sharing scheme is widely used in retail markets such as [22]. The wholesale pricing scheme is widely used in newsvendor models such as [16].

[6]We consider a simplified but rather general model, where the QoS of a user is a linear function of the expected data rate.

of the spectrum licensee Π^{SL} and the database Π^{DB}, which are defined as the difference between the revenue obtained by providing the services and the cost, are given as follow. The payoffs under the RSS scheme (Scheme I) are

$$\begin{cases} \Pi^{\mathrm{SL}} \triangleq \Pi^{\mathrm{SL}}_{(\mathrm{I})} = (\pi_{\mathrm{L}} - c_{\mathrm{L}})\eta_{\mathrm{L}}(1-\delta) \\ \Pi^{\mathrm{DB}} \triangleq \Pi^{\mathrm{DB}}_{(\mathrm{I})} = (\pi_{\mathrm{A}} - c_{\mathrm{A}})\eta_{\mathrm{A}} + (\pi_{\mathrm{L}} - c_{\mathrm{L}})\eta_{\mathrm{L}}\delta, \end{cases} \tag{2}$$

and under the WPS scheme (Scheme II) are

$$\begin{cases} \Pi^{\mathrm{SL}} \triangleq \Pi^{\mathrm{SL}}_{(\mathrm{II})} = (\pi_{\mathrm{L}} - w)\eta_{\mathrm{L}} - c_{\mathrm{L}}\eta_{\mathrm{L}}, \\ \Pi^{\mathrm{DB}} \triangleq \Pi^{\mathrm{DB}}_{(\mathrm{II})} = \pi_{\mathrm{A}}\eta_{\mathrm{A}} + w\eta_{\mathrm{L}} - c_{\mathrm{A}}\eta_{\mathrm{A}}. \end{cases} \tag{3}$$

C. Positive and Negative Network Externalities

Network externalities arise when a user's experiencing of consuming a service/product depends on the behavior of other users in the same network [21]. In the integrated market that we study, there coexist two types of network externalities. The *negative* network externality characterizes the user performance degradation due to an increased level of congestion. The *positive* network externality corresponds to the increasing quality of the (advanced) information as more users purchase the information. Next we analytically quantify these two network externalities. As $\eta_{\mathrm{A}} + \eta_{\mathrm{B}} + \eta_{\mathrm{L}} = 1$, sometimes we also denote the total fraction of users using unlicensed TV channels as $1 - \eta_{\mathrm{L}}$ in the rest of the paper.

We first have the following observations for a user's expected utility of three strategy choices:

- *L is a constant independent of η_{A}, η_{B}, and η_{L}.* This is because a user can access to the licensed channel exclusively, hence the communication performance on such a channel does not depend on the choices of others.
- *B is non-increasing in $1 - \eta_{\mathrm{L}}$ (the total fraction of users using unlicensed TV channels) due to the congestion effect.* This is because the unlicensed TV channels must be used in a shared manner, hence more users using these channels increases the level of congestion (interference) and reduces the performance of each user. We denote the congestion effect caused by users using the same unlicensed TV channels as *negative network externality*.
- *A is non-increasing in $1-\eta_{\mathrm{L}}$, due to the negative network externality*. This is because the unlicensed TV channels are shared by users, independent of their choices of subscribing to the database's advanced service or not.
- *A is non-decreasing in η_{A}*. As more users subscribe to the database's advanced service, the more information (*e.g.,* users channel choices and transmission power levels) the database knows. In such case, the database can estimate more accurate channel information, which benefits the users who subscribe to the advanced service. The detailed explanation is provided in [36]. Such benefit that increases with the users choosing the advanced service is called the *positive network externality*.

We write B as a non-increasing function of $1 - \eta_{\mathrm{L}}$, *i.e.,*

$$B(\eta_{\mathrm{L}}) \triangleq f(1 - \eta_{\mathrm{L}}). \tag{4}$$

We write A as the combination of a non-increasing function of $1 - \eta_{\mathrm{L}}$ and a non-decreasing function of η_{A}, *i.e.,*

$$A(\eta_{\mathrm{A}}, \eta_{\mathrm{L}}) \triangleq f(1 - \eta_{\mathrm{L}}) + g(\eta_{\mathrm{A}}). \tag{5}$$

Function $f(\cdot)$ reflects the congestion effect, and is identical for B and A (as users experience the same congestion effect in both basic and advanced services). Function $g(\cdot)$ reflects the performance gain induced by the advanced information, *i.e.,* the (advanced) information value.

We have the following natural assumption:

Assumption 1: The expected utilities achieved by choosing different services satisfy

$$L > A(\eta_{\mathrm{A}}, \eta_{\mathrm{L}}) > B(\eta_{\mathrm{L}}).$$

Comparing with unlicensed TV channels, there is no congestion on the licensed TV channels. Hence, the expected utility provided by the leasing service is larger than that provided by the advanced service (*i.e.,* $L > A(\eta_{\mathrm{A}}, \eta_{\mathrm{L}})$ and $L > B(\eta_{\mathrm{L}})$). As advanced information provides benefit to the users, we have $A(\eta_{\mathrm{A}}, \eta_{\mathrm{L}}) > B(\eta_{\mathrm{L}})$.[7]

We further introduce the following assumptions on functions $f(\cdot)$ and $g(\cdot)$.

Assumption 2: Function $f(\cdot)$ is non-negative, non-increasing, convex, and continuously differentiable.

Assumption 3: Function $g(\cdot)$ is non-negative, non-decreasing, concave, and continuously differentiable.

Due to the increasing marginal performance degradation under congestion, we assume that function $f(\cdot)$ is non-increasing and convex. Such assumption is widely used to model the network congestion effect in wireless networks (see, *e.g.,* [23], [24], and references therein). Because of the diminishing marginal performance improvement induced by the advanced information, we assume that function $g(\cdot)$ is non-decreasing and concave. Note that the above generic functions $f(\cdot)$ and $g(\cdot)$ can potentially model a wide range of scenarios where advanced information has different meanings. We will provide more detailed discussions in [36].

D. Three-Stage Interaction Model

Based on the above discussion, an integrated spectrum and information market involves the interactions among the database, the spectrum licensee, and the users. Hence, we formulate the interactions as a three-stage hierarchical model as shown in Figure 2.

Specifically, Stage I captures the negotiation process between the database and the spectrum licensee, who negotiate the commission charge details of the spectrum market platform, *i.e.,* the revenue sharing factor δ under RSS, or the wholesale price w under WPS. Stage II studies the price competition between the database and the spectrum licensee,

[7] If we set $L < B(\eta_{\mathrm{L}})$, no one will choose the leasing service even the leasing service is free of charge. In this case, our integrated model degenerates to the pure information market that is analyzed in [7]. If we set $A(\eta_{\mathrm{A}}, \eta_{\mathrm{L}}) = B(\eta_{\mathrm{L}})$, then no user will choose the advanced service even the database provides the advanced service for free. In this case, our integrated model degenerates to a simpler market, where the licensee provides the leasing service and the database provides the basic service only. The analysis of such a model is simpler than the most general case that we consider here.

Stage I: Commission Negotiation
The database and the spectrum licensee negotiate the commission charge details (*i.e.,* δ under RSS or w under WPS).

⇓

Stage II: Price Competition Game
The database determines the information price $\pi_{\rm A}$;
The spectrum licensee determines the channel price $\pi_{\rm L}$.

⇓

Stage III: User Behavior and Market Dynamics
The users determine and update their choices according to best responses;
The market evolves to an equilibrium point.

Fig. 2. Three-stage Interaction Model.

where the database determines the advanced information price $\pi_{\rm A}$, and the spectrum licensee determines the leasing licensed channel price $\pi_{\rm L}$. Stage III focuses on the subscription behaviors of users, where each user makes his best choice, and dynamically updates the subscription choice based on the current market shares.

In the following sections, we will use backward induction to analyze this three-stage interaction model.

IV. Stage III – User Behavior and Market Equilibrium

In this section, we study the user behavior and market dynamics in Stage III, given the database's information price $\pi_{\rm A}$ and the licensee's channel price $\pi_{\rm L}$ (in Stage II). In the following, we first discuss the user's best response choice, then show how the user behavior dynamically evolves, finally discuss how the market converges to an equilibrium point.

A. User's Best Response

Equations (1), (4) and (5) show that users' choices of services depend on the current market shares of different services. Hence given the market shares, users can compute their best response choices, which in turn will affect the market shares. Next we will characterize such a process in details.

For convenience, we introduce a virtual time-discrete system with slots $t = 1, 2, \ldots$, where users change their decisions at the beginning of every slot, based on the market shares at the end of the previous time slot.[8] Let $(\eta_{\rm L}^t, \eta_{\rm A}^t, \eta_{\rm B}^t)$ denote the market shares at the end of slot t satisfying $(\eta_{\rm L}^t, \eta_{\rm A}^t) \in \Omega$, where Ω is the market share feasible set defined as $\Omega = \{(\eta_{\rm L}, \eta_{\rm A}) \in \mathbb{R}_+^2 | \eta_{\rm L} + \eta_{\rm A} \le 1\}$. For convenience, we assume that θ is uniformly distributed in $[0, 1]$ for all users.[9] As each user will choose a strategy that maximizes its payoff

[8] The purpose of introducing the virtual time-discrete system is to characterize the relation between the price and the market equilibrium, and to facilitate the calculation of database's optimal price strategy later. Such an analysis technique has been extensively adopted in the existing literature, e.g., [25].

[9] Uniform assumption has been frequently used in the past networking literature (*e.g.,* [23]), and the relaxation to more general distribution often does not change the main insights.

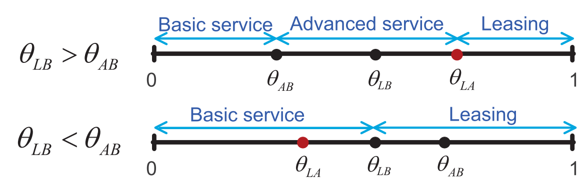


Fig. 3. Illustration of $\theta_{\rm LB}$, $\theta_{\rm AB}$, and $\theta_{\rm LA}$.

defined in (1), a type-θ user's best response is

$$\begin{cases} s_\theta^* = \mathsf{l}, & \text{iff } \theta L - \pi_{\rm L} > \max\{\theta A(\eta_{\rm A}^t, \eta_{\rm L}^t) - \pi_{\rm A},\ \theta \cdot B(\eta_{\rm L}^t)\}, \\ s_\theta^* = \mathsf{a}, & \text{iff } \theta A(\eta_{\rm A}^t, \eta_{\rm L}^t) - \pi_{\rm A} > \max\{\theta L - \pi_{\rm L},\ \theta \cdot B(\eta_{\rm L}^t)\}, \\ s_\theta^* = \mathsf{b}, & \text{iff } \theta B(\eta_{\rm L}^t) > \max\{\theta L - \pi_{\rm L},\ \theta A(\eta_{\rm A}^t, \eta_{\rm L}^t) - \pi_{\rm A}\}, \end{cases} \tag{6}$$

where $B(\eta_{\rm L}^t) = f(1-\eta_{\rm L}^t)$ and $A(\eta_{\rm A}^t, \eta_{\rm L}^t) = f(1-\eta_{\rm L}^t) + g(\eta_{\rm A}^t)$.

To better illustrate the above best response, we introduce the following notations:

$$\theta_{\rm LB}^t \triangleq \frac{\pi_{\rm L}}{L - B(\eta_{\rm L})}, \quad \theta_{\rm AB}^t \triangleq \frac{\pi_{\rm A}}{A(\eta_{\rm A}, \eta_{\rm L}) - B(\eta_{\rm L})}, \\ \theta_{\rm LA}^t \triangleq \frac{\pi_{\rm L} - \pi_{\rm A}}{L - A(\eta_{\rm A}, \eta_{\rm L})}. \tag{7}$$

The above three notations denote three user type thresholds. For example, $\theta_{\rm LB}^t$ is defined as the type of user who is indifferent between choosing the leasing service and the basic service (i.e., both services provide the user with the same expected payoff). Combining these three user types thresholds together, we can compute the market share of each service.

Figure 3 illustrates several possible relationships among $\theta_{\rm LB}^t$, $\theta_{\rm AB}^t$, and $\theta_{\rm LA}^t$. Intuitively, the users with low values of θ are more willing to choose the free basic service. The users with medium values of θ are willing to choose the advanced service, in order to achieve a relatively large utility with a relatively low service cost. The users with high values of θ are more willing to choose the leasing service so that they can obtain a large utility. Notice that we have $\theta_{\rm LB}^t < \theta_{\rm AB}^t$ if the information price $\pi_{\rm A}$ is high or the information value $A(\eta_{\rm A}^t, \eta_{\rm L}^t) - B(\eta_{\rm L}^t)$ is low. Then, no user chooses the advanced service, as shown in the bottom subfugure in Figure 3.

Next we characterize the market shares in slot $t+1$ due to users' best responses. This can help us understand the user behaviour dynamics and market evolutions in the next subsection. As we assume that θ is uniformly distributed in $[0, 1]$, the newly derived market shares $\{\eta_{\rm L}^{t+1}, \eta_{\rm A}^{t+1}\}$ in slot $t+1$, given any market shares $\{\eta_{\rm L}^t, \eta_{\rm A}^t\}$ at the end of t, are

- If $\theta_{\rm LB}^t > \theta_{\rm AB}^t$, then $\eta_{\rm L}^{t+1} = 1 - \theta_{\rm LA}^t$ and $\eta_{\rm A}^{t+1} = \theta_{\rm LA}^t - \theta_{\rm AB}^t$;
- If $\theta_{\rm LB}^t \le \theta_{\rm AB}^t$, then $\eta_{\rm L}^{t+1} = 1 - \theta_{\rm LB}^t$ and $\eta_{\rm A}^{t+1} = 0$.

We summarize this in Lemma 1.

Lemma 1: Given any pair of market shares $(\eta_{\rm L}^t, \eta_{\rm A}^t) \in \Omega$ at the end of slot t, the derived pair of market shares $(\eta_{\rm L}^{t+1}, \eta_{\rm A}^{t+1}) \in \Omega$ in slot $t+1$ are given by

$$\begin{cases} \eta_{\rm L}^{t+1} = \max\left\{1 - \max\{\theta_{\rm LA}^t, \theta_{\rm LB}^t\},\ 0\right\}, \\ \eta_{\rm A}^{t+1} = \max\left\{\min\{\theta_{\rm LA}^t, 1\} - \theta_{\rm AB}^t,\ 0\right\}, \end{cases} \tag{8}$$

where $\theta_{\rm LB}^t$, $\theta_{\rm AB}^t$, and $\theta_{\rm LA}^t$ are given in (7).

Under the assumption that all users update the best responses once synchronously, we can get the results in Lemma 1. Due to the stringent page limit of JSAC, we provide all the proofs in [36]. Since θ_{LB}^t, θ_{AB}^t, and θ_{LA}^t are functions of market shares $\{\eta_{\mathrm{L}}^t, \eta_{\mathrm{A}}^t\}$, the derived market shares $\{\eta_{\mathrm{L}}^{t+1}, \eta_{\mathrm{A}}^{t+1}\}$ in slot $t+1$ are also functions of $\{\eta_{\mathrm{L}}^t, \eta_{\mathrm{A}}^t\}$, and hence can be written as $\eta_{\mathrm{L}}^{t+1}(\eta_{\mathrm{L}}^t, \eta_{\mathrm{A}}^t)$ and $\eta_{\mathrm{A}}^{t+1}(\eta_{\mathrm{L}}^t, \eta_{\mathrm{A}}^t)$.

B. Market Dynamics and Equilibrium

When the market shares change, the users' payoffs (on the advanced service and basic service) change accordingly, as both $A(\eta_{\mathrm{A}}^t, \eta_{\mathrm{L}}^t)$ and $B(\eta_{\mathrm{L}}^t)$ change. As a result, users will update their best responses repeatedly, hence the market shares will evolve dynamically until reaching a stable point (called *market equilibrium*). In this subsection, we will study such a market dynamics and equilibrium, given fixed prices $\{\pi_{\mathrm{L}}, \pi_{\mathrm{A}}\}$ (which are decided in Stage II).

Base on the analysis in Section IV-A, let $(\eta_{\mathrm{L}}^0, \eta_{\mathrm{A}}^0) \in \Omega$ denote the *initial market shares* in slot $t=0$ and $(\eta_{\mathrm{L}}^t, \eta_{\mathrm{A}}^t) \in \Omega$ denote the market shares derived at the end of slot t (which serve as the initial market shares for the next slot $t+1$). We further denote $\triangle\eta_{\mathrm{L}}$ and $\triangle\eta_{\mathrm{A}}$ as the changes (dynamics) of market shares between two successive time slots, *e.g.,* t and $t+1$, that is,

$$\begin{cases} \triangle\eta_{\mathrm{L}}(\eta_{\mathrm{L}}^t, \eta_{\mathrm{A}}^t) = \eta_{\mathrm{L}}^{t+1} - \eta_{\mathrm{L}}^t, \\ \triangle\eta_{\mathrm{A}}(\eta_{\mathrm{L}}^t, \eta_{\mathrm{A}}^t) = \eta_{\mathrm{A}}^{t+1} - \eta_{\mathrm{A}}^t, \end{cases} \tag{9}$$

where $(\eta_{\mathrm{L}}^{t+1}, \eta_{\mathrm{A}}^{t+1}) \in \Omega$ are the derived market share in slot $t+1$, and can be computed by Lemma 1.

Obviously, if both $\triangle\eta_{\mathrm{L}}$ and $\triangle\eta_{\mathrm{A}}$ are zero in a slot $t+1$, *i.e.,* $\eta_{\mathrm{L}}^{t+1} = \eta_{\mathrm{L}}^t$ and $\eta_{\mathrm{A}}^{t+1} = \eta_{\mathrm{A}}^t$, then users will no longer change their strategies in the future. This implies that the market achieves the *market equilibrium*. Formally,

Definition 1 (Market Equilibrium): A pair of market shares $\boldsymbol{\eta}^* = \{\eta_{\mathrm{L}}^*, \eta_{\mathrm{A}}^*\} \in \Omega$ *is a market equilibrium, if and only if*

$$\triangle\eta_{\mathrm{L}}(\eta_{\mathrm{L}}^*, \eta_{\mathrm{A}}^*) = 0, \quad \textit{and} \quad \triangle\eta_{\mathrm{A}}(\eta_{\mathrm{L}}^*, \eta_{\mathrm{A}}^*) = 0. \tag{10}$$

Next, we study the existence and uniqueness of the market equilibrium, and further characterize the market equilibrium analytically. These results will help us analyze the price competition game in Stage II (Section V).

Proposition 1 (Existence and Uniqueness): Given any feasible price pair $(\pi_{\mathrm{L}}, \pi_{\mathrm{A}})$*, there exists at least one market equilibrium* $(\eta_{\mathrm{L}}^*, \eta_{\mathrm{A}}^*) \in \Omega$*. Furthermore, the market equilibrium is unique and the market dynamics globally converges to it starting from any initial point* $\{\eta_{\mathrm{L}}^0, \eta_{\mathrm{A}}^0\} \in \Omega$ *if*

$$\max_{(\eta_{\mathrm{L}},\eta_{\mathrm{A}})\in\Omega} \frac{g'(\eta_{\mathrm{A}})}{g(\eta_{\mathrm{A}})} \cdot \frac{L - B(\eta_{\mathrm{L}})}{L - A(\eta_{\mathrm{A}}, \eta_{\mathrm{L}})} \le \frac{1}{\kappa}, \tag{11}$$

where $\kappa = \max_{(\eta_{\mathrm{L}},\eta_{\mathrm{A}})\in\Omega}\{\frac{\pi_{\mathrm{L}}-\pi_{\mathrm{A}}}{L-A(\eta_{\mathrm{A}},\eta_{\mathrm{L}})}, \frac{\pi_{\mathrm{A}}}{A(\eta_{\mathrm{A}},\eta_{\mathrm{L}})-B(\eta_{\mathrm{L}})}\}$*, and* $g'(\eta_{\mathrm{A}})$ *is the first-order derivative of* $g(\cdot)$ *with respect to* η_{A}*.*

We prove the convergence of this market dynamics based on the contraction mapping theorem [32], with the detailed proof in [36]. A practical implication of condition (11) is that the existence of a unique equilibrium requires the information value $g(\eta_{\mathrm{A}})$ (which corresponds to positive network externality) increases slowly with η_{A}. Note that the condition (11) is sufficient but not necessary for the uniqueness. Our numerical simulations show that the market converges to a unique equilibrium for a wide range of prices, even when the condition (11) is violated. Nevertheless, the sufficient condition in (11) suggests that there could be multiple equilibrium points if the impact of positive network externality is significant.

Suppose the uniqueness condition (11) is satisfied. We characterize the unique equilibrium by the following theorem.

Theorem 1 (Market Equilibrium): Suppose the uniqueness condition (11) holds. Then, for any feasible price pair $(\pi_{\mathrm{L}}, \pi_{\mathrm{A}})$*,*

(a) *If* $\theta_{\mathrm{LB}}(\eta_{\mathrm{L}}, \eta_{\mathrm{A}})|_{\eta_{\mathrm{L}}=0} \le \theta_{\mathrm{AB}}(\eta_{\mathrm{L}}, \eta_{\mathrm{A}})|_{\eta_{\mathrm{A}}=0}$*, there is a unique market equilibrium* $\boldsymbol{\eta}^\dagger = \{\eta_{\mathrm{L}}^\dagger, \eta_{\mathrm{A}}^\dagger\}$ *satisfies*

$$\eta_{\mathrm{L}}^\dagger = 1 - \theta_{\mathrm{LB}}(\eta_{\mathrm{L}}^\dagger, \eta_{\mathrm{A}}^\dagger), \quad \textit{and} \quad \eta_{\mathrm{A}}^\dagger = 0; \tag{12}$$

(b) *If* $\theta_{\mathrm{LB}}(\eta_{\mathrm{L}}, \eta_{\mathrm{A}})|_{\eta_{\mathrm{L}}=0} > \theta_{\mathrm{AB}}(\eta_{\mathrm{L}}, \eta_{\mathrm{A}})|_{\eta_{\mathrm{A}}=0}$*, there is a unique market equilibrium* $\boldsymbol{\eta}^* = \{\eta_{\mathrm{L}}^*, \eta_{\mathrm{A}}^*\}$ *satisfies*

$$\begin{aligned} \eta_{\mathrm{L}}^* &= 1 - \theta_{\mathrm{LA}}(\eta_{\mathrm{L}}^*, \eta_{\mathrm{A}}^*), \\ \eta_{\mathrm{A}}^* &= \theta_{\mathrm{LA}}(\eta_{\mathrm{L}}^*, \eta_{\mathrm{A}}^*) - \theta_{\mathrm{AB}}(\eta_{\mathrm{L}}^*, \eta_{\mathrm{A}}^*). \end{aligned} \tag{13}$$

For the detailed proof, please refer to [36]. A practical implication of Theorem 1 is that the information price π_{A} should not be too high or the information value (i.e., $A - B$) should be large enough; otherwise, no users will choose the advance service at the equilibrium.

V. Stage II – Price Competition Game Equilibrium

In this section, we study the price competition between the database and the spectrum licensee in Stage II, given the commission negotiation solution in Stage I. Based on the analysis of Stage III in Section IV, the database and spectrum licensee are able to predict the user behavior and market equilibrium in Stage III when making their pricing decisions. We will analyze the pricing equilibrium under both the revenue sharing scheme (RSS) and the wholesale price scheme (WPS).

Definition 2 (Price Competition Game): The Price Competition Game (PCG) is defined as follows.

- Players: *The database and the spectrum licensee;*
- Strategies: *Information price* $\pi_{\mathrm{A}} \ge 0$ *for the database, and* $\pi_{\mathrm{L}} \ge 0$ *for the licensee;*
- Payoffs: *Payoff is defined in (2) under RSS, and in (3) under WPS.*

For the rest of this section, we assume that condition (8) holds. Then, we write the unique market equilibrium $\boldsymbol{\eta}^* = \{\eta_{\mathrm{L}}^*, \eta_{\mathrm{A}}^*\}$ in Stage III as functions of prices $(\pi_{\mathrm{L}}, \pi_{\mathrm{A}})$, *i.e.,* $\eta_{\mathrm{L}}^*(\pi_{\mathrm{L}}, \pi_{\mathrm{A}})$ and $\eta_{\mathrm{A}}^*(\pi_{\mathrm{L}}, \pi_{\mathrm{A}})$. Intuitively, we can interpret η_{L}^* and η_{A}^* as the *demand* functions of the licensee and the database, respectively.

A. Revenue Sharing Scheme — RSS

We fist study the game equilibrium under RSS, where the licensee shares a fixed percentage $\delta \in [0, 1]$ of revenue with the database. By (2), the payoffs of the licensee and the database can be written as:

$$\begin{cases} \Pi_{(\mathrm{I})}^{\mathrm{SL}}(\pi_{\mathrm{L}}, \pi_{\mathrm{A}}) = (\pi_{\mathrm{L}} - c_{\mathrm{L}}) \cdot \eta_{\mathrm{L}}^*(\pi_{\mathrm{L}}, \pi_{\mathrm{A}}) \cdot (1 - \delta), \\ \Pi_{(\mathrm{I})}^{\mathrm{DB}}(\pi_{\mathrm{L}}, \pi_{\mathrm{A}}) = (\pi_{\mathrm{A}} - c_{\mathrm{A}})\eta_{\mathrm{A}}^*(\pi_{\mathrm{L}}, \pi_{\mathrm{A}}) \\ \qquad\qquad + (\pi_{\mathrm{L}} - c_{\mathrm{L}})\eta_{\mathrm{L}}^*(\pi_{\mathrm{L}}, \pi_{\mathrm{A}})\delta. \end{cases} \tag{14}$$

Definition 3 (Price Equilibrium): A price pair $(\pi_{\rm L}^*, \pi_{\rm A}^*)$ is a Nash equilibrium, if

$$\begin{cases} \pi_{\rm L}^* = \arg\max\limits_{\pi_{\rm L}\geq 0}\ \Pi_{\rm (I)}^{\rm SL}(\pi_{\rm L}, \pi_{\rm A}^*), \\ \pi_{\rm A}^* = \arg\max\limits_{\pi_{\rm A}\geq 0}\ \Pi_{\rm (I)}^{\rm DB}(\pi_{\rm L}^*, \pi_{\rm A}). \end{cases} \tag{15}$$

It is difficult to analytically characterize the market equilibrium $\{\eta_{\rm L}^*(\pi_{\rm L}, \pi_{\rm A}), \eta_{\rm A}^*(\pi_{\rm L}, \pi_{\rm A})\}$ under a particular price pair $\{\pi_{\rm L}, \pi_{\rm A}\}$. We tackle this challenge by transforming the original price competition game (PCG) into an equivalent *market share competition game* (MSCG). Then the market shares are the strategies of the database and the licensee, while the prices are the functions of the market shares.

A key observation of such a transformation is that, under the uniqueness condition (11), there is a *one-to-one* correspondence between the market equilibrium $\{\eta_{\rm L}^*, \eta_{\rm A}^*\}$ and the prices $\{\pi_{\rm L}, \pi_{\rm A}\}$. Because of this, once the licensee and the database choose the prices $\{\pi_{\rm L}, \pi_{\rm A}\}$, they have equivalently chosen the market shares $\{\eta_{\rm L}^*, \eta_{\rm A}^*\}$. Substitute $\theta_{\rm LA} = \frac{\pi_{\rm L}-\pi_{\rm A}}{L-A}$ and $\theta_{\rm AB} = \frac{\pi_{\rm A}}{A-B}$ into (13), we can derive the inverse function of (13), where prices are functions of market shares defined on $\mathbf{\Omega}$, *i.e.,*.[10]

$$\begin{cases} \pi_{\rm L}(\eta_{\rm L}, \eta_{\rm A}) = (1-\eta_{\rm L})\cdot(L - f(1-\eta_{\rm L}) - g(\eta_{\rm A})) \\ \qquad\qquad\qquad + (1-\eta_{\rm L}-\eta_{\rm A})\cdot g(\eta_{\rm A}), \\ \pi_{\rm A}(\eta_{\rm L}, \eta_{\rm A}) = (1-\eta_{\rm L}-\eta_{\rm A})\cdot g(\eta_{\rm A}). \end{cases} \tag{16}$$

The payoffs of the database and the licensee are rewritten as:

$$\begin{cases} \widetilde{\Pi}_{\rm (I)}^{\rm SL}(\eta_{\rm L}, \eta_{\rm A}) = (\pi_{\rm L}(\eta_{\rm L}, \eta_{\rm A}) - c_{\rm L})\cdot\eta_{\rm L}\cdot(1-\delta), \\ \widetilde{\Pi}_{\rm (I)}^{\rm DB}(\eta_{\rm L}, \eta_{\rm A}) = (\pi_{\rm A}(\eta_{\rm L}, \eta_{\rm A}) - c_{\rm A})\eta_{\rm A} \\ \qquad\qquad\qquad + (\pi_{\rm L}(\eta_{\rm L}, \eta_{\rm A}) - c_{\rm L})\eta_{\rm L}\delta. \end{cases} \tag{17}$$

Definition 4 (Market Share Competition Game): The equivalent Market Share Competition Game (MSCG) is defined as

- Players: *The database and the spectrum licensee;*
- Strategies: *Market share $\eta_{\rm A}$ for the database, and $\eta_{\rm L}$ for the licensee, where $(\eta_{\rm L}, \eta_{\rm A}) \in \mathbf{\Omega}$;*
- Payoffs: *Payoffs are defined in (17).*

Definition 5 (Market Share Equilibrium): Market shares $(\eta_{\rm L}^*, \eta_{\rm A}^*) \in \mathbf{\Omega}$ is a Market Share Equilibrium if

$$\begin{aligned} \eta_{\rm L}^* &= \arg\max_{\eta_{\rm L}} \Pi_{\rm (I)}^{\rm SL}(\eta_{\rm L}, \eta_{\rm A}^*), \\ \text{and } \eta_{\rm A}^* &= \arg\max_{\eta_{\rm A}} \Pi_{\rm (I)}^{\rm DB}(\eta_{\rm L}^*, \eta_{\rm A}). \end{aligned} \tag{18}$$

We first show that the equivalence between the original PCG and the above MSCG.

Proposition 2 (Equivalent Games): If $\{\eta_{\rm L}^*, \eta_{\rm A}^*\}$ is a Market Share Equilibrium of MSCG, then $\{\pi_{\rm L}^*, \pi_{\rm A}^*\}$ given by (16) is a Price Equilibrium of PCG.

We next characterzie the Market Share Equilibrium of the MSCG. We first give the following proposition which bounds the market shares maximizing the database's and the licensee's expected payoffs in (18).

[10]Note that we omit the trivial case in (12), where the database has a zero market share in terms of the advanced service. In this case, the licensee can determine the market share splitting (between leasing service and basic service from the database) by optimizing his leasing price $\pi_{\rm L}$.

Proposition 3 (Boundary of Market Share Equilibrium): For any $\{\eta_{\rm L}^*, \eta_{\rm A}^*\}$ that is a solution of (18), we have $\eta_{\rm L}^* \in (0, 1/2)$ and $\eta_{\rm L}^* + \eta_{\rm A}^* < 1$.

Proposition 3 shows that the licensee will achieve an equilibrium market share that is smaller than half. Intuitively, the objective of the licensee is to maximize its own profit, and a larger market share of licensee corresponds to a smaller market price, which does not necessarily increase the licensee's profit. Another key insight of Proposition 3 is that considering (18) alone is enough to guarantee the feasibility constraint of $(\eta_{\rm L}, \eta_{\rm A}) \in \mathbf{\Omega}$ in Definition 5. Hence, we can study the existence and uniqueness of the MSCG market share equilibrium by analyzing (18) only.

Theorem 2 (Existence and Uniqueness of Market Share Equilibrium): Given the commission charge δ, there exists at least one Market Share Equilibrium of MSCG $(\eta_{\rm L}^*, \eta_{\rm A}^*) \in \mathbf{\Omega}$. Furthermore, a sufficient condition for the uniqueness of the market share equilibrium is, for $\forall(\eta_{\rm L}, \eta_{\rm A}) \in \mathbf{\Omega}$, we have

$$\frac{\partial^2\widetilde{\Pi}_{\rm (I)}^{\rm SL}(\eta_{\rm L}, \eta_{\rm A})}{\partial{\eta_{\rm L}}^2} \leq \frac{\partial^2\widetilde{\Pi}_{\rm (I)}^{\rm SL}(\eta_{\rm L}, \eta_{\rm A})}{\partial\eta_{\rm L}\partial\eta_{\rm A}}$$

and

$$\frac{\partial^2\widetilde{\Pi}_{\rm (I)}^{\rm DB}(\eta_{\rm L}, \eta_{\rm A})}{\partial{\eta_{\rm A}}^2} \leq \frac{\partial^2\widetilde{\Pi}_{\rm (I)}^{\rm DB}(\eta_{\rm L}, \eta_{\rm A})}{\partial\eta_{\rm A}\partial\eta_{\rm L}}, \tag{19}$$

Proof Sketch: First, we can prove that the MSCG is a supermodular game, and thus has at least one Nash Equilibrium. Based on the supermodular game theory [11], the MSCG has a unique Nash Equilibrium as long as it satisfies the sufficient condition given in (19). □

For a supermodular game with a unique Nash equilibrium, several commonly used updating rules are guaranteed to converged to the NE [11]. In this paper, we use the best response algorithm as in [26]. Due to the space limit, we provide the detailed algorithm in [36].

Once we obtain the Market Share Equilibrium $(\eta_{\rm L}^*, \eta_{\rm A}^*)$ of MSCG, we can compute the Price Equilibrium $(\pi_{\rm L}^*, \pi_{\rm A}^*)$ of the original PCG by (16).

B. Wholesale Pricing Scheme — WPS

We now study the game equilibrium under WPS, where the database charges a fixed wholesale price $w \geq 0$ from each successful transaction of the licensee. By (3), the payoffs of the licensee and the database can be written as:

$$\begin{cases} \Pi_{\rm (II)}^{\rm SL}(\pi_{\rm L}, \pi_{\rm A}) = (\pi_{\rm L} - w)\cdot\eta_{\rm L}^*(\pi_{\rm L}, \pi_{\rm A}) - c_{\rm L}\eta_{\rm L}^*(\pi_{\rm L}, \pi_{\rm A}), \\ \Pi_{\rm (II)}^{\rm DB}(\pi_{\rm L}, \pi_{\rm A}) = (\pi_{\rm A} - c_{\rm A})\cdot\eta_{\rm A}^*(\pi_{\rm L}, \pi_{\rm A}) + w\cdot\eta_{\rm L}^*(\pi_{\rm L}, \pi_{\rm A}). \end{cases} \tag{20}$$

With the similar analysis used in Section V-A, we can transform the Price Competiton Game (PCG) into an equivalent Market Share Competition Game (MSCG), and show that the MSCG is a supermodular game. Our key results about the existence and uniqueness of game equilibrium are as follows.

Theorem 3: Given the wholesale price w, there exists a unique Market Share Equilibrium $\eta_{\rm L}^* \in (0, 1/2)$ and $\eta_{\rm L}^* + \eta_{\rm A}^* < 1$ for the MSCG, and thus a unique Price

Equilibrium, if the following conditions are satisfied for $\forall(\eta_{\mathrm{L}}, \eta_{\mathrm{A}}) \in \boldsymbol{\Omega}$,

$$\frac{\partial^2 \widetilde{\Pi}^{\mathrm{SL}}_{(\mathrm{II})}(\eta_{\mathrm{L}}, \eta_{\mathrm{A}})}{\partial \eta_{\mathrm{L}}{}^2} \le \frac{\partial^2 \widetilde{\Pi}^{\mathrm{SL}}_{(\mathrm{II})}(\eta_{\mathrm{L}}, \eta_{\mathrm{A}})}{\partial \eta_{\mathrm{L}} \partial \eta_{\mathrm{A}}}$$

and

$$\frac{\partial^2 \widetilde{\Pi}^{\mathrm{DB}}_{(\mathrm{II})}(\eta_{\mathrm{L}}, \eta_{\mathrm{A}})}{\partial \eta_{\mathrm{A}}{}^2} \le \frac{\partial^2 \widetilde{\Pi}^{\mathrm{DB}}_{(\mathrm{II})}(\eta_{\mathrm{L}}, \eta_{\mathrm{A}})}{\partial \eta_{\mathrm{A}} \partial \eta_{\mathrm{L}}}, \tag{21}$$

Although we use the similar method to derive the Nash equilibrium of the PCG game under both RSS and WPS, these two equilibria are quite different. Intuitively, under RSS, the objective of the database is consistent with that of the licensee. This can be shown by the common term in both players' payoffs given in (14). Hence, the database becomes less aggressive in competing with spectrum licensee under RSS that under WPS.

To emphasize the fact that the equilibrium payoffs in Stage II depend on δ (under RSS) or w (under WPS), we will write the equilibrium payoff of the database as $\Pi^{\mathrm{DB}}_{(\mathrm{I})}(\delta)$ under RSS and $\Pi^{\mathrm{DB}}_{(\mathrm{II})}(w)$ under WPS. Similarly, we will write the equilibrium payoff of the licensee as $\Pi^{\mathrm{SL}}_{(\mathrm{I})}(\delta)$ under RSS and $\Pi^{\mathrm{SL}}_{(\mathrm{II})}(w)$ under WPS.

VI. Stage I – Commission Bargaining Solution

In this section, we study the commission negotiation among the database and the spectrum licensee in Stage I, based on their predictions of the price equilibrium in Stage II and the market equilibrium in Stage III.[11]

Specifically, we want to find a feasible revenue sharing percentage $\delta \in [0, 1]$ under RSS, or a feasible wholesale price $w \ge 0$ under WPS, that is *satisfactory* for both the database and the spectrum licensee. This is motivated by the fact that both the database operator (*e.g.,* Google, Microsoft, and SpectrumBridge) and spectrum licensees (*e.g.,* AT&T, Verizon, and China Mobile) have considerable market power, and one side can not determine δ or w alone. We formulate the commission negotiation problem as a *bargaining problem*, and solve it using the Nash bargaining theory [10].

A. Revenue Sharing Percentage δ-Bargaining Under RSS

We first study RSS, where we want to determine the revenue sharing percentage $\delta \in [0, 1]$.

We first derive the database's and the licensee's payoffs when reaching an agreement and when *not* reaching any agreement. This allows us to characterize the payoff improvements due to successful bargaining.

Formally, when reaching an agreement δ, the database's and the licensee's payoffs are $\Pi^{\mathrm{DB}}_{(\mathrm{I})}(\delta)$ and $\Pi^{\mathrm{SL}}_{(\mathrm{I})}(\delta)$ derived in Section V-A, respectively. When not reaching any agreement (reaching the disagreement), the licensee's profit is $\Pi^{\mathrm{SL}}_0 = 0$, and the database's profit is $\Pi^{\mathrm{DB}}_0 = \pi^{\dagger}_{\mathrm{A}} \cdot \eta^{\dagger}_{\mathrm{A}}(\pi^{\dagger}_{\mathrm{A}})$, where $\pi^{\dagger}_{\mathrm{A}}$ and $\eta^{\dagger}_{\mathrm{A}}(\pi^{\dagger}_{\mathrm{A}})$ are the database's optimal price and the corresponding market share in the pure information market.[12]

[11]In our proposed bargaining model, the database and the licensee only conduct the bargaining if this leads to a payoff increase for both sides. Otherwise they choose not to bargain and do not cooperate in Stage I.

[12]Such an optimal price and the corresponding market share can be derived in the same way as in Section V-A, by simply setting $\theta_{\mathrm{LA}} = 1$.

Then, the Nash bargaining solution is the solution of the following optimziation problem,

$$\begin{aligned} &\max_{\delta \in [0,1]} \ \left(\Pi^{\mathrm{DB}}_{(\mathrm{I})}(\delta) - \Pi^{\mathrm{SL}}_0\right) \cdot \left(\Pi^{\mathrm{SL}}_{(\mathrm{I})}(\delta) - \Pi^{\mathrm{DB}}_0\right) \\ &\text{s. t. } \Pi^{\mathrm{DB}}_{(\mathrm{I})}(\delta) \ge \Pi^{\mathrm{SL}}_0, \quad \Pi^{\mathrm{SL}}_{(\mathrm{I})}(\delta) \ge \Pi^{\mathrm{DB}}_0. \end{aligned} \tag{22}$$

Analytically solving (22) may be difficult, if we are not able to analytically characterize $\Pi^{\mathrm{DB}}_{(\mathrm{I})}(\delta)$ and $\Pi^{\mathrm{SL}}_{(\mathrm{I})}(\delta)$. Nevertheless, we notice that the bargaining variable δ lies in a closed and bounded range of $[0, 1]$, and the objective function of (22) is bounded. Hence, there exists at least one optimal solution for (22). As our numerical results show that the objective function of (22) is approximately quadratic in δ, the optimal solution is unique and can be found by using one-dimensional search methods (*e.g.,* [27]).

B. Wholesale Price w-Bargaining Under WPS

We now study WPS, where the database charges the spectrum licensee a fixed wholesale price $w \ge 0$ for each successful transaction of the latter.

When reaching an agreement w, the database's and the licensee's payoffs are $\Pi^{\mathrm{DB}}_{(\mathrm{II})}(w)$ and $\Pi^{\mathrm{SL}}_{(\mathrm{II})}(w)$ derived in Section V-B, respectively. When not reaching any agreement (reaching the disagreement), the licensee's profit is $\Pi^{\mathrm{SL}}_0 = 0$, and the database's profit is $\Pi^{\mathrm{DB}}_0 = \pi^{\dagger}_{\mathrm{A}} \cdot \eta^{\dagger}_{\mathrm{A}}(\pi^{\dagger}_{\mathrm{A}})$, which is same as that under RSS (Section VI-A). The Nash bargaining problem is

$$\begin{aligned} &\max_{w \ge 0} \ \left(\Pi^{\mathrm{DB}}_{(\mathrm{II})}(w) - \Pi^{\mathrm{SL}}_0\right) \cdot \left(\Pi^{\mathrm{SL}}_{(\mathrm{II})}(w) - \Pi^{\mathrm{DB}}_0\right) \\ &\text{s. t. } \Pi^{\mathrm{DB}}_{(\mathrm{II})}(w) \ge \Pi^{\mathrm{SL}}_0, \quad \Pi^{\mathrm{SL}}_{(\mathrm{II})}(w) \ge \Pi^{\mathrm{DB}}_0. \end{aligned} \tag{23}$$

We further notice that that we can restrict the bargaining variable w within a closed and bounded set, say $[0, L]$, while not affecting the optimality of the solution. This is no user will choose the leasing service when $w > L$, in which case the spectrum licensee will get a zero payoff. This is certainly not an optimal solution of (23). Similar as Section VI-A, there would exist a unique solution for (23) as shown in our simulations, and which can be found effectively through one-dimensional numerical search.

VII. Simulation Result

We evaluate the system performance (*e.g.,* the database's profit and the network profit) achieved under both revenue sharing scheme (RSS) and wholesale price scheme (WPS) through numerical studies. We will focus on the impact of system parameters (*i.e.,* the degree of network externality and the licensee's operating cost) on system performance.

A. Simulation Setting

As a concrete example, we choose $f(\eta_{\mathrm{L}}) = \alpha_1 - \beta_1 \cdot (1 - \eta_{\mathrm{L}})^{\gamma_1}$ to model the negative network externality with the following justifications. First, when $\eta_{\mathrm{L}} = 1$, there is no congestion among users choosing unlicensed TV channels, as all users lease licensed TV channels for exclusive usage. In this case, the utility provided by the basic service is α_1.

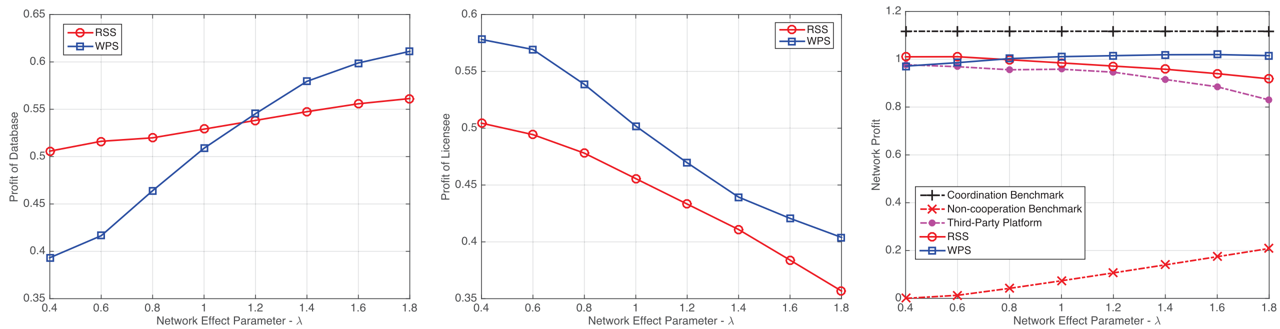


Fig. 4. (a) The database's profit, (b) The licensee's profit, (c) Network profit vs the level of network externality λ under the revenue sharing scheme (RSS) and the wholesale price scheme (WPS).

Second, when $\eta_{\rm L} = 0$, all users choose the shared unlicensed TV channels, and the congestion is maximum. In this case, the utility provided by the basic service decreases to $\alpha_1 - \beta_1$. Finally, the parameter $\gamma_1 \in (0, 1]$ models the elasticity of the negative network externality. A small γ_1 means that the value of $f(\eta_{\rm L})$ will be small even with a large $\eta_{\rm L}$. This means that a small fraction of users using unlicensed TV channels will cause a large enough congestion.

Similarly, we use function $g(\eta_{\rm A}) = \alpha_2 + (\beta_2 - \alpha_2) \cdot {\eta_{\rm A}}^{\gamma_2}$ to model the positive network externality. Specifically, α_1 denotes the minimum benefit brought by the database's advanced information on unlicensed TV channels occupation, and β_2 denotes the maximum benefit brought by the database's advanced information. The parameter $\gamma_2 \in (0, 1]$ characterizes the elasticity of the positive network externality.[13]

To characterize the interaction of negative and positive network externality in the information market, we first derive the first-order derivative of A with respect to $\eta_{\rm A}$, *i.e.,* $\frac{\partial A}{\partial \eta_{\rm A}} = -\gamma_1 \cdot \beta_1 \cdot (\eta_{\rm A} + \eta_{\rm B})^{\gamma_1 - 1} + \gamma_2 \cdot \beta_2 \cdot (\eta_{\rm A})^{\gamma_2 - 1}$. Notice that if $\frac{\partial A}{\partial \eta_{\rm A}} > 0$, the value of advance information increases with the market share $\eta_{\rm A}$ (*i.e.,* the percentage of users purchasing the advanced information). We call this the *positive network externality dominant* case (or simply positive dominant). On the other hand, if $\frac{\partial A}{\partial \eta_{\rm A}} < 0$, the value of advance information decreases with the market share $\eta_{\rm A}$. We call this the *negative network externality dominant* case (or simply negative dominant).

To facilicate our study, we set $\gamma_1 = \gamma_2$ and change the value of β_1 and β_2 to examine different cases of network externality. Specifically, we use $\lambda = \beta_2/\beta_1$ to represent the degree of network externality. Obviously, if $\lambda = \beta_2/\beta_1 > (\frac{\eta_{\rm A}+\eta_{\rm B}}{\eta_{\rm A}})^{1-\gamma_1}$, then $\frac{\partial A}{\partial \eta_{\rm A}} > 0$ for any $\{\eta_{\rm A}, \eta_{\rm B}\}$, hence the information market is positive dominant. If $\lambda < (\frac{\eta_{\rm A}+\eta_{\rm B}}{\eta_{\rm A}})^{1-\gamma_1}$, then $\frac{\partial A}{\partial \eta_{\rm A}} < 0$, hence the information market is negative dominant. Hence an increasing value of λ implies that the positive network externality is getting relatively stronger.

Unless specified otherwise, we assume that $\alpha_1 = 1$, $\alpha_2 = 1$, $\beta_1 = 1$, $\gamma_1 = 0.6$, $\gamma_2 = 0.6$, and $c_{\rm A} = 0.2$ in the rest of the numerical studies.

[13]These two functions generalize the linear network externality models from many existing literatures such as [28], satisfy our Assumptions 2 and 3, and are used to model the network effect in the literature (see, *e.g.,* [29]).

B. The Impact of Network Effect Parameter λ

Figure 4 illustrates (a) the database's profit, (b) the licensee's profit, and (c) the network profit, *i.e.,* the aggregate profit of the database and the licensee achieved under different network effect. Here we choose λ from 0.4 to 1.8, *i.e.,* the network effect changes from strong negative externality to strong positive externality. In this simulation, we fix the licensee's operational cost as $c_{\rm L} = 0.9$ and the quality of leasing service as $L = 6$.

In Figure 4.c, we use the black dash-dot line (with mark $+$) to denote the *coordination benchmark*, where the database and the licensee act as an integrated party to maximize their aggregate profit. We use the red dash-dot line (with mark $\times$) to denote the *non-cooperation benchmark* (with pure information market only), where the database does not display the licensee's licensed TV channel information. The brown dash-dot line (with mark $\bullet$) denotes the case where the licensee sells channels on *a third-party spectrum market platform*, where the licensee can display his licensed information for free. In a third-party scheme, the licensee displays his licensed information in a third-party platform, instead of using the database's platform. Comparing with the three-stage model, such a third-party model degenerates to a two-stage model, where the database and the licensee compete with each other for selling information or channels to users in Stage I, and users decide the best subscription decisions in Stage II.

The key observations from Figure 4 are as follows.

Observation 1:

(a) *The database's profits achieved under both schemes increase with λ (Figure 4.a), while the licensee's profits decrease with λ (Figure 4.b).*

(b) *When the negative network externality is dominant (λ is small), RSS is a better choice for the database; When the positive network externaltiy is dominant (λ is large), WPS is a better choice for the database (Figure 4.a).*

(c) *WPS always benefits the licensee (Figure 4.b).*

(d) *The proposed RSS and WPS alway outperform the non-cooperation scheme and the third-party scheme in terms of network profit.* (e.g., *the performance gain between WPS and the non-cooperation scheme is up to 87%). Meanwhile, both schemes can achieve a network profit close to the co-ordinated benchmark (Figure 4.c).*

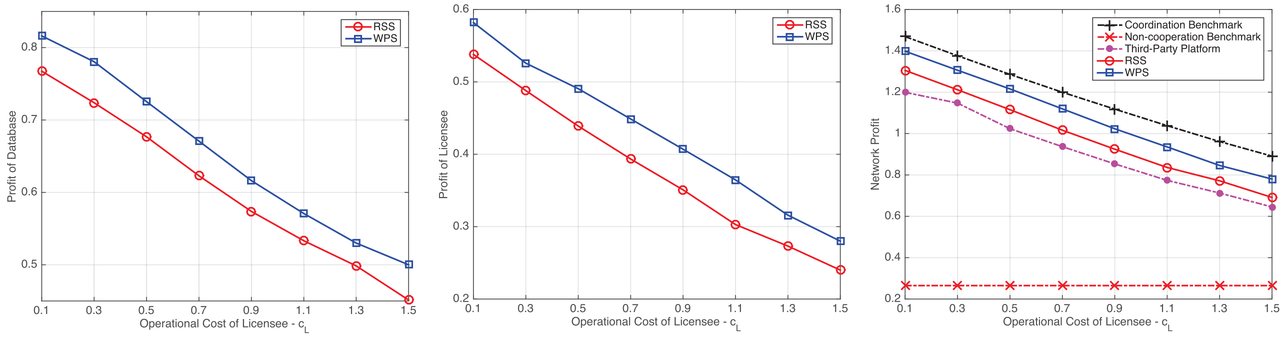


Fig. 5. (a) The database's profit, (b) The licensee's profit, (c) Network profit vs the licensee's operational cost c_{L} under the revenue sharing scheme (RSS) and the wholesale price scheme (WPS).

In the following, we discuss the the intuitions behind each observation in detail.

Observation 1(a): When the positive network externality becomes stronger, the advanced service provides a higher utility to users. Such a higher utility drives the equilibrium price as well as the equilibrium market share up for the database, which results in the increase of the database's profit. To keep the leasing service attractive, the licensee needs to drive the equilibrium retail price down, which results in the decrease of the licensee's profit.

Observation 1(b): As the objective of the database and the licensee are partially coordinated under RSS [33], the price competition under WPS is more severe than that under RSS. When the negative network externality is dominant, the increase of the database's market share may severely decrease the quality of advanced service. In this case, it is better for the database to let the licensee take a large fraction of the market share and share the revenue of the licensee through RSS. On the other hand, when the positive network externality is dominant, a larger market share can significantly increase the attractiveness of the database. Hence the database is able to get a higher profit with the more aggressive WPS.

Observation 1(c): As the database charges a fixed price per transaction to the licensee under WPS, the licensee can enjoy the full benefit of putting effort to maximize its own profit (*e.g.,* increasing the leasing service price to serve a minority of users with high values of θ). Under RSS, however, some benefit from serving users would go to the database, as the licensee needs to share a fixed portion of the revenue with the database. In such case, the licensee would like to exert a higher effort under WPS than RSS, hence can achieve a higher payoff under WPS.

Observation 1(d): Under our proposed schemes (*i.e.,* RSS and WPS), the database and the licensee negotiate with each other in Stage I. The third-party scheme does not involve such negotiation process and can not exploit the cooperation benefit, hence performs worse than our proposed schemes. Compared to the pure information market, letting some users to lease the licensed TV channels alleviates the congestion (interference) of the unlicensed TV channels. Hence, the database can provide a good quality of service to users at a higher price, which increases the network profit. The performance gap between the two proposed schemes and coordination benchmark is caused by the *imperfect* coordination of the database and the licensee. The database and licensee cooperate but do not completely coordinate (*i.e.,* act as a single decision maker), and we refer to this gap as the *non-coordination loss*.

We want to emphasize that even though the pure cooperation model can achieve the maximum network profit, the regulators such as FCC in the United States and Ofcom in UK would not allow the licensee to be a database. The rational for this is to prevent the monopoly in the market that may jeopardize the interest of end-users.

C. The Impact of the Licensee's Operational Cost c_L

Figure 5 is similar as Figures 4, except that here we focus on the impact of licensee's operational cost c_{L} (which incorporates costs due to energy consumptions). We choose c_{L} from 0.1 to 1.5, and fix the degree of network externality as $\lambda = 1.8$ (*i.e.,* the positive network externality is dominant) and the quality of leasing service as $L = 6$.

We list the key observations from Figure 5 as follows.

Observation 2:

(a) *The database's and the licensee's profits achieved under both schemes decrease with the licensee's operational cost c_{L} (Figures 5.a and 5.b).*

(b) *The non-coordination loss between the proposed two schemes and the coordination benchmark increases with the licensee's operational cost c_{L} (Figure 5.c).*

(c) *The performance gain between the proposed two schemes and the non-cooperation pure information market decreases with the licensee's operational cost c_{L} (Figure 5.c).*

we discuss the intuitions of each observation as follows.

Observation 2(a): As the licensee's operational cost increases, the licensee needs to increase its service price, which results in the decrease of the licensee's market share and the profit. Meanwhile, the database's revenue earned from the licensee decreases, and thus leads to the decrease of the database's profit.

Observation 2(b): Due to the increase of the licensee's operational cost, the licensee may not be willing to provide the leasing service. Hence, it is more difficult to reach an agreement during the negotiation process in Stage I, which results in a high non-coordination loss.

Observation 2(c): As the licensee would raise the service price in order to compensate its revenue loss due to its higher operational cost, the leasing service becomes less attractive to users. With the decreased benefit brought by the spectrum market, the proposed schemes becoming increasingly similar as the pure information market.

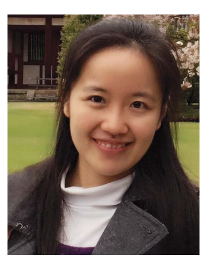
VIII. Conclusion

Relying database to detect the dynamically changing radio environment can not only reduce the energy consumption of the unlicensed radio devices, but also can effectively help the devices to balance the energy consumption and communication quality. Hence, the database-assisted TV white space network is a promising commercial applications of green cognitive communication technology. As the success of such a network replies on a carefully designed business model, we propose a database-provided integrated spectrum and information market, and analyzed the interactions among the geo-location database, the licensee, and the unlicensed users systematically. Our work characterizes what commission charge scheme is better in terms of maximizing database's and licensee's own profits under different degrees of network externality. Specifically, when the negative network externality is dominant, RSS is a better choice for the database, while WPS is a better choice for the licensee. When the positive network externality is dominant, WPS is a better choice for both the database and the licensee.

There are several possible directions to extend this work. For example, we can investigate an oligopoly scenario with multiple databases and licensees. Such an oligopoly scenario involves the formulation of a much more challenging one-to-many bargaining problem [34], [35].

References

[1] G. Gür and F. Alagöz, "Green wireless communications via cognitive dimension: An overview," *IEEE Netw.*, vol. 25, no. 2, pp. 50–56, Mar./Apr. 2011.
[2] M. Webb, "Smart 2020: Enabling the low carbon economy in the information age," The Climate Group, London, U.K., Jun. 2008.
[3] *Third Memorandum Opinion and Order*, document FCC 12-36, Federal Communications Commission, Washington, DC, USA, 2012.
[4] *Implementing Geolocation*, Ofcom, London, U.K., Feb. 2015.
[5] X. Feng, Q. Zhang, and J. Zhang, "Hybrid pricing for TV white space database," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 1995–2003.
[6] Y. Luo, L. Gao, and J. Huang, "Price and inventory competition in oligopoly TV white space markets," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 5, pp. 1002–1013, May 2015.
[7] Y. Luo, L. Gao, and J. Huang, "Trade information, not spectrum: A novel TV white space information market model," in *Proc. IEEE WiOpt*, May 2014, pp. 405–412.
[8] Y. Luo, L. Gao, and J. Huang, "MINE GOLD to deliver green cognitive communications," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 2, pp. 2749–2760, Dec. 2015.
[9] Y. Luo, L. Gao, and J. Huang, "Business modeling for TV white space networks," *IEEE Commun. Mag.*, vol. 53, no. 5, pp. 82–88, May 2015.
[10] J. F. Nash, Jr., "The bargaining problem," *Econometrica*, vol. 18, no. 2, pp. 155–162, 1950.
[11] D. M. Topkis, *Supermodularity and Complementarity*. Princeton, NJ, USA: Princeton Univ. Press, 1998.
[12] A. M. Brandenburger and B. J. Nalebuff, *Co-Opetition*. Danvers, MA, USA: Crown Publishing Group, 2011.
[13] M. Hafeez and J. M. H. Elmirghani, "Green licensed-shared access," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 12, pp. 2579–2595, Dec. 2015.
[14] J. Palicot, "Cognitive radio: An enabling technology for the green radio communications concept," in *Proc. ACM IWCMC*, 2009, pp. 489–494.
[15] Z. Ji, I. Ganchev, M. O'Droma, and X. Zhang, "A realisation of broadcast cognitive pilot channels piggybacked on T-DMB," *Trans. Emerg. Telecommun. Technol.*, vol. 24, nos. 7–8, pp. 709–723, 2013.
[16] D. Niyato and E. Hossain, "Spectrum trading in cognitive radio networks: A market-equilibrium-based approach," *IEEE Wireless Commun.*, vol. 15, no. 6, pp. 71–80, Dec. 2008.
[17] L. Gao, X. Wang, Y. Xu, and Q. Zhang, "Spectrum trading in cognitive radio networks: A contract-theoretic modeling approach," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 4, pp. 843–855, Apr. 2011.
[18] L. Gao, J. Huang, Y.-J. Chen, and B. Shou, "An integrated contract and auction design for secondary spectrum trading," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 3, pp. 581–592, Mar. 2013.
[19] A. W. Min, X. Zhang, J. Choi, and K. G. Shin, "Exploiting spectrum heterogeneity in dynamic spectrum market," *IEEE Trans. Mobile Comput.*, vol. 11, no. 12, pp. 2020–2032, Dec. 2012.
[20] K. Zhu, E. Hossain, and D. Niyato, "Pricing, spectrum sharing, and service selection in two-tier small cell networks: A hierarchical dynamic game approach," *IEEE Trans. Mobile Comput.*, vol. 13, no. 8, pp. 1843–1856, Aug. 2014.
[21] H. K. Bhargava and V. Choudhary, "Economics of an information intermediary with aggregation benefits," *Inf. Syst. Res.*, vol. 15, no. 1, pp. 22–36, 2004.
[22] G. P. Cachon and M. A. Lariviere, "Contracting to assure supply: How to share demand forecasts in a supply chain," *Manage. Sci.*, vol. 47, no. 5, pp. 629–646, 2001.
[23] N. Shetty, G. Schwartz, and J. Walrand, "Internet QoS and regulations," *IEEE/ACM Trans. Netw.*, vol. 18, no. 6, pp. 1725–1737, Dec. 2010.
[24] R. Johari, G. Y. Weintraub, and B. Van Roy, "Investment and market structure in industries with congestion," *Oper. Res.*, vol. 58, no. 5, pp. 1303–1317, 2010.
[25] S. Ren and M. van der Schaar, "Data demand dynamics in wireless communications markets," *IEEE Trans. Signal Process.*, vol. 60, no. 4, pp. 1986–2000, Apr. 2012.
[26] J. Huang, R. A. Berry, and M. L. Honig, "Distributed interference compensation for wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 5, pp. 1074–1084, May 2006.
[27] N. Nisan, T. Roughgarden, E. Tardos, and V. V. Vazirani, Eds., *Algorithmic Game Theory*. Cambridge, U.K.: Cambridge Univ. Press, 2007.
[28] D. Easley and J. Kleinberg, *Networks, Crowds, and Markets: Reasoning About a Highly Connected World*. Cambridge, U.K.: Cambridge Univ. Press, 2012.
[29] W. Wu, R. T. B. Ma, and J. C. S. Lui, "Exploring bundling sale strategy in online service markets with network effects," in *Proc. IEEE INFOCOM*, Apr./May 2014, pp. 442–450.
[30] N. B. Chang and M. Liu, "Optimal channel probing and transmission scheduling for opportunistic spectrum access," *IEEE/ACM Trans. Netw.*, vol. 17, no. 6, pp. 1805–1818, Dec. 2009.
[31] H. Jiang, L. Lai, R. Fan, and H. V. Poor, "Optimal selection of channel sensing order in cognitive radio," *IEEE Trans. Wireless Commun.*, vol. 8, no. 1, pp. 297–307, Jan. 2009.
[32] D. P. Bertsekas and J. N. Tsitsiklis, *Parallel and Distributed Computation: Numerical Methods*. Belmont, MA, USA: Athena Scientific, 1989.
[33] J. D. Dana, Jr., and K. E. Spier, "Revenue sharing and vertical control in the video rental industry," *J. Ind. Econ.*, vol. 49, no. 3, pp. 223–245, 2001.
[34] L. Gao, G. Iosifidis, J. Huang, L. Tassiulas, and D. Li, "Bargaining-based mobile data offloading," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1114–1125, Jun. 2014.
[35] H. Yu, M. H. Cheung, and J. Huang, "Cooperative Wi-Fi deployment: A one-to-many bargaining framework," in *Proc. IEEE WiOpt*, May 2015, pp. 347–354.
[36] Y. Luo, L. Gao, and J. Huang. (2016). "An integrated spectrum and information market for green cognitive communications." [Online]. Available: http://arxiv.org/abs/1603.04982



Yuan Luo (S'10–M'16) received the Ph.D. degree from the Chinese University of Hong Kong in 2015. She is currently a Post-Doctoral Research Fellow with The Chinese University of Hong Kong. Her research interests are in the field of wireless communications and network economics, with current emphasis on TV white space networks and crowdsourcing. She is a recipient of the Best Paper Award in the IEEE WiOpt 2014, the CUHK Postgraduate Research Output Award 2015, and the CUHK Young Scholar Thesis Award 2015.

Lin Gao (S'08–M'10) received the M.S. and Ph.D. degrees in Electronic Engineering from Shanghai Jiao Tong University, China, in 2006 and 2010, respectively. He was a Post-Doctoral Fellow with The Chinese University of Hong Kong from 2010 to 2015. He is currently an Associate Professor with the Harbin Institute of Technology, Shenzhen, China. His research interests are in the interdisciplinary area combining telecommunications and microeconomics, with particular focus on the game-theoretic and economic analysis for various communication and network scenarios, including cognitive radio networks, TV white space networks, heterogeneous networks, cooperative communications, 5G communications, mobile crowdsensing, and mobile Internet. He is a recipient of the Best Paper Award from the IEEE WiOpt in 2013, 2014 and 2015.

Jianwei Huang (S'01–M'06–SM'11–F'16) is currently an Associate Professor with the Department of Information Engineering, The Chinese University of Hong Kong. He has co-authored five books and six ESI highly cited papers. He has served as an Associate Editor of the IEEE TRANSACTIONS ON COGNITIVE COMMUNICATIONS AND NETWORKING, the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, and the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS-Cognitive Radio Series. He is a Distinguished Lecturer of the IEEE Communications Society. He is the co-recipient of eight international best paper awards, including the IEEE Marconi Prize Paper Award in Wireless Communications in 2011.