PAPER

A Spectrum Sharing Method Based on Users' Behavior and Providers' Profit

Kazuhiko KINOSHITA[†a)], ***Member***, **Yukika MARUYAMA**[††], ***Student Member***, **Keita KAWANO**[†††], ***and*** **Takashi WATANABE**[††], ***Members***

SUMMARY In recent years, spectrum sharing has received much attention as a technique for more efficient spectrum use. In the case in which all providers are cooperative, spectrum sensing can easily be realized and can improve user throughput (on average). If that is not the case, providers are not cooperative, i.e., spectrum trading, spectrum bands are rented to promote spectrum sharing. To ensure more profit, however, non-cooperative providers must correctly estimate the fluctuation of the number of connected users to be able to determine the offered channel price. In this paper, we propose a spectrum sharing method to achieve both higher throughput and provider profit via appropriate pricing using a disaggregate behavioral model. Finally, we confirm the effectiveness of the proposed method using simulation experiments.

key words: *dynamic spectrum allocation, spectrum sharing, user behavior, provider profit*

1. Introduction

The mobile communication environment has improved significantly with recent advances in wireless transmission technologies such as WiFi [1], WiMAX [2], and LTE [3]. The number of mobile users worldwide is approaching saturation; however, the amount of mobile traffic continues to rapidly increase because people are making ever-increasing use of multimedia services, e.g., music and movies, via mobile networks on smartphones. Therefore, significantly more spectral resources are needed to maintain and improve the quality of services provided to users. However, spectral resources, which are appropriate for data communication, are limited, such that this shortage has become an important problem [4].

In heterogeneous wireless networks, the spectrum sharing technique dynamically assigns spectrum channels to primary systems (PSs, i.e., licensees, spectrum owners) and to secondary systems (SSs), which have no priority access to the channel [5]. When there are multiple secondary systems in an area covered by the primary system, the total wireless communication capacity of the area increases, because two or more secondary systems can use the same spectrum if they are not adjacent.

In the case in which all providers are cooperative, spectrum sharing can be realized easily, which improves user throughput (on average) [6]. In the case in which providers are not cooperative, the primary system does not share the spectrum, because the user throughput of the primary system degrades. Therefore, spectrum trading in which spectrum bands are bought and sold by systems is used to promote spectrum sharing [7]. Pricing plays an important role in spectrum trading because it indicates the value of the spectrum resources and determines assignments.

The market equilibrium approach is one possible method for solving the pricing problem [8]. Based on market theory, the price is set such that it balances the supply and demand for spectrum resources. As a result, both primary and secondary systems are satisfied with the price. However, in studies using the market equilibrium approach, providers charge connected users using price per bandwidth or achieved throughput so as to guess the profit and losses caused by spectrum sharing. Therefore, these methods cannot be applied to current widespread communication environments such as monthly fixed fee model where a user pays a constant charge for his/her communications regardless of its traffic volume or throughput.

Under fixed fees for users, the revenue of the system depends on the fluctuation in the number of users connected to the system. For this reason, systems must correctly estimate the fluctuation in the number of connected users and use the fluctuation to determine an adequate price to ensure greater profit surely. Therefore, it is important to accurately model user behavior.

In this paper, we propose a spectrum sharing method to achieve both higher throughput and increased provider profit based on careful control of pricing. The user behavior of the selecting system is modeled using a random utility model that utilizes a stochastic decision process. To estimate user behavior, systems exploit a disaggregate behavioral model. The parameters of the disaggregate behavioral model can be estimated from the data consisting of alternatives chosen by users and the condition of systems at the selection time. To maximize profit, a secondary system sets the offering channel price to a value less than the increase in revenue obtained for the estimation. Additionally, the primary system decides the number of assignment channels and which secondary systems are targets of channel assignment (without interference), and maximizes the profit of the system.

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[†]The author is with Tokushima University, Tokushima-shi, 770-8506 Japan.
[††]The authors are with Osaka University, Suita-shi, 565-0871 Japan.
[†††]The author is with Okayama University, Okayama-shi, 700-8530 Japan.
a) E-mail: kazuhiko@is.tokushima-u.ac.jp

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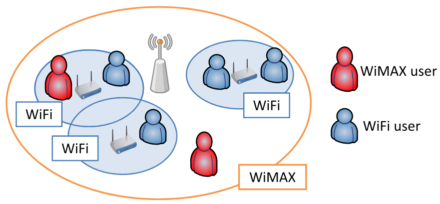

Fig. 1 Access point selection in WiMAX/WiFi integrated network.

2. Related Works

2.1 Heterogeneous Wireless Network

Although several wireless network systems have been developed independently of each other, they should be integrated for seamless access by users. Therefore, integrated networks such as WiMAX and WiFi integrated networks [9], [10] have been actively studied. In integrated networks, high-quality communication is achievable using two or more network systems as complementary access resources. In [9], the potential of the integration of WiMAX and residential WiFi access is shown, in addition to the win–win situation for both WiFi and WiMAX operators.

As shown in Fig. 1, in the integrated network, a mobile user obtains access to the best wireless system, which is chosen based on the criteria of the user (e.g., application and mobility) and the system (e.g., traffic congestion). For example, a moving user should be assigned to a WiMAX network so as to obtain continuous coverage. On the other hand, a user in an urban area with heavy traffic should be connected to a WiFi network so as to obtain higher throughput. Therefore, users can have better communications and systems can achieve load balancing [10].

In addition, to achieve seamless accesses, not only horizontal handover (meaning switching an access point within the same type of system) but also vertical handover (meaning switching between different systems) [11] are performed.

2.2 Spectrum Sharing

Integrated wireless networks assume that each wireless system uses the spectrum band that is prescribed by law, such that even if one system temporarily has unused spectrum resources, they cannot be used by another system. To overcome this problem, dynamic spectrum access (DSA) technology, also referred to as dynamic spectrum management, has received much attention [12].

DSA significantly increases opportunities for spectrum sharing. New types of spectrum sharing enabled by DSA include higher-power transmission at times when the primary systems in a band area are inactive, trading of spectrum access rights, and collaboration among secondary systems [13].

In this paper, we focus on spectrum property rights [12] in spectrum sharing in which providers trade spectrum-exclusive access rights to use spectrum resources. On this occasion, a spectrum owner (or primary system) assigns its licensed spectrum to secondary systems, which have no priority access to the band. Because two or more secondary systems can use the same spectrum when they are not adjacent, the total wireless communication capacity increases.

To search for an assignment pattern without interference between adjacent systems, a centralized control server [14]–[16] controls spectrum allocation and access procedures. In [16], a centralized server called the spectrum manager controls the spectrum assignment and collects the information necessary for assignment.

From a game theoretical perspective, spectrum sharing can be classified based on spectrum allocation behaviors, i.e., cooperative or non-cooperative [17]. Cooperative providers always cooperate with each other to reach a common goal such as the maximization of total throughput. On the other hand, non-cooperative providers aim to maximize their own interests.

In the following section, spectrum sharing methods for cooperative and non-cooperative providers are explained.

(1) Spectrum Sharing Method for Cooperative Providers

In game theory, a cooperative game is a game in which groups of players enforce cooperative behavior. In such a cooperative environment, primary and secondary systems cooperate with each other to increase social welfare. The simple real-world situation is that in which the same provider owns both primary and secondary systems.

According to [6] spectrum sharing improves the average user throughput. The method exploits the number of users who connect to the systems as the evaluation value of the genetic algorithm (GA). By using GA under the constraint that it disallow assignment of the same spectrum to adjacent access points, it is possible to assign channels without interference among selected access points.

In general, however, providers are usually selfish to obtain higher profit, so that they are NOT cooperative.

(2) Spectrum Sharing Method for Non-Cooperative Providers

Non-cooperative (or competitive, selfish) providers independently make decisions and pursue their own profit. Because spectrum sharing degrades the primary system throughput because of the decrease in the primary available spectrum, spectrum trading methods are proposed. This method adopts money trading as a motivation for spectrum sharing [8]. Price, therefore, plays an important role in spectrum trading because it indicates the value of the spectrum resources and determines assignments.

To solve the pricing problem, several approaches such as auctions [18], market equilibria [19], and learning algorithms [20] have been used. In [18], each secondary system bids for an additional channel. In [19], the price is set such that it balances the supply and demand for the spectrum. [20] proposed an optimal pricing scheme for bandwidth sharing in WiMAX/WiFi integrated networks using the Stackelberg game and learning algorithms. The Stackelberg equilibrium is defined as the strategy profile that maximizes the primary's payoff while the secondary players play their best responses. The learning algorithm is adopted for secondary systems to store information regarding user bandwidth demands in the population and update the demand function (e.g., the price-demand function) until profit for the secondary systems is maximized.

In fact, however, such a pay-as-you-go-based charging system is not widely used and a monthly fixed fee model is typically applied. In a fixed fee system, a provider has no need to have such a short-term motivation.

2.3 User Model

We describe the *disaggregate behavioral model* [21] that is widely used in the civil engineering planning field to predict user behaviors.

Disaggregate behavioral modeling provides mathematical representations of traveler preferences to estimate the utility or value that travelers place on different features or benefits. Unlike aggregate modeling, disaggregate behavioral modeling can use fewer samples, and thus, it is used widely as a technique to predict the chosen action in transportation and civil engineering planning [22]. In addition, several existing studies adopt disaggregate behavioral modeling to choose among communication systems [23], [24]. The model is based on *the random utility model*, in which the preference for each choice of named utility is introduced and in which preference stochastically fluctuates.

The random utility model of choice is an econometric representation of maximizing behavior. This model regards utility as stochastically fluctuating, such that, alternatively, the utility might change. Mathematically, the model is simply performs utility maximization where utility is treated as a random function.

Symbolically, let Γ be a set of alternatives and U be a set of real-valued functions defined over the elements of Γ. Then, the random model asserts that for a decision-maker faced with a choice set $I \in \Gamma$, there exists a utility function U_i used to select an alternative $i \in I$, given by

$$U_i = V_i + \epsilon_i, \tag{1}$$

where V_i is the observed final real part and ϵ_i is the unknown realization of a random variable ϵ. Finally, the probability q_i of selecting the alternative i is given by the following equation:

$$q_i = \text{Prob}\,[U_i \le U_j,\ \forall j \in I,\ j \ne i]. \tag{2}$$

Among random utility models, the most successful method was proposed by McFadden [21]. He assumed that the random parts of utility functions are independent and identically Gumbel distributed, as given by

$$\text{Prob}\,[\epsilon_i \ge \epsilon] = e^{-e^{-(\epsilon+\alpha_i)}}. \tag{3}$$

His specification yields the logit model, which is given by the following equation:

$$q_i = \frac{e^{V_i-\alpha_i}}{\sum_{j\in I} e^{V_j-\alpha_j}}. \tag{4}$$

In applications, V_i, which is the deterministic part of the utility function, is always assumed to be linear-in-parameters with an additive disturbance representation; α_i is modeled as a fixed number, independently of person. Because this postulate absorbs a random portion of the utility, q_i and V_i can be written as

$$q_i = \frac{e^{V_i}}{\sum_{j\in I} e^{V_j}}, \tag{5}$$

$$V_i = \sum_l \theta_l X_{il}, \tag{6}$$

where parameter θ is to be estimated and X_{il} is the lth attribute for alternative i. θ_l is a coefficient of disaggregate behavioral model. It is a kind of weight to indicate the impact of attribute l. In other words, larger θ_l means X_l is more influential for users' decision.

To apply the disaggregate behavioral model to network selection, we consider a scenario in which a user chooses an action from among connecting to the primary system, connecting to the secondary system, and cancelling the connection. This set of choices means that if there is a user who can connect to either WiMAX or WiFi, the choice set I consists of: alternative 1, to connect to the primary system (WiMAX); alternative 2, to connect to the secondary system (WiFi); and alternative 3, to not connect to any systems.

Let s_i denote a system selected based on alternative i. Then, s_1 is the primary system (p) and s_2 is the secondary system (s). In the state of system s_i in which the number of users connecting to system is n and the number of available channels is c, the determinate utility for a user to choose i in Eq. (6) can be represented as follows:

$$V_1(n,c) = \theta_1 t^{(p)}(n,c), \tag{7}$$

$$V_2(n,c) = \theta_1 t^{(s)}(n,c), \tag{8}$$

$$V_3 = \theta_2 ASC, \tag{9}$$

where we assume that the first attribute $t^{s_i}(n,c)$ is the expected communication time per bit and the second attribute ASC (alternative-specific constant) is a constant for alternative 3.

The attribute $t^{s_i}(n,c)$ can be calculated as an inverse of the instantaneous system throughput as

$$t^{s_i}(n,c) = \frac{n}{Qc}, \tag{10}$$

where Q is the communication capacity of the system per a channel.

We assume that the longer t^{s_i} is, the smaller the selected probability becomes; therefore, $\theta_1 < 0$. Note that θ_2 is the parameter that indicates the strength of the influence of the constant ASC on the utility.

From Eq. (5), the probability that a user selects the alternative i is given by

$$q_i(n^{(p)}, c^{(p)}, n^{(s)}, c^{(s)}) = \frac{e^{V_i(n^{s_i}, c^{s_i})}}{e^{V_1(n^{(p)}, c^{(p)})} + e^{V_2(n^{(s)}, c^{(s)})} + e^{V_3}}. \tag{11}$$

2.4 Problematic Issues

Between non-cooperative providers, spectrum sharing methods using money trading as a motivation for primary provider to share spectrum have been proposed. By sharing the spectrum, primary providers can obtain additional profit by lending channels, and secondary providers can increase their effective spectrum bandwidth and user throughput. In these methods, however, providers charge connected users based on either a price per bandwidth or an achieved throughput, so as to guess the profit and loss caused by the spectrum sharing. In addition, the total number of connected users is fixed, and therefore, this environment is restrictive. Therefore, these methods cannot apply to current widespread communication environments, for example, monthly fixed fee models.

3. Proposed Method

3.1 Spectrum Sharing Network

To reasonably trade spectrum resources under a fixed-fee system, we propose a spectrum sharing network. It gives a motivation of spectrum sharing and leads to efficient use of spectrum resources. As shown in Fig. 2 where PS and SS mean PS provider and SS provider, respectively, this network consists of users, providers, and a broker that controls the fee paid by users, acting as a fair mediator to both providers. The fee distribution from the broker to providers corresponds to the amount information transferred; thus, providers can act under the fixed user fee model, i.e., as if they were under a specific rent environment.

To simultaneously assign spectrum channels to more than one secondary system without interference, the total communication capacity must increase.

Figure 3 shows the overview of spectrum sharing procedure in the proposed network.

Each player, i.e., user, broker, primary system, and secondary system, acts as follows.

(1) User

By subscribing to a sharing network with a fixed fee beforehand, a user can connect to either primary or secondary networks. In order to select the best system to connect, user throughput should be expected beforehand. It can be realized by some related works such as [25]. Figure 4 shows the flowchart of user's behavior.

(2) Broker

As mentioned above, the task of the broker is to collect fees from users and dispense them to providers corresponding

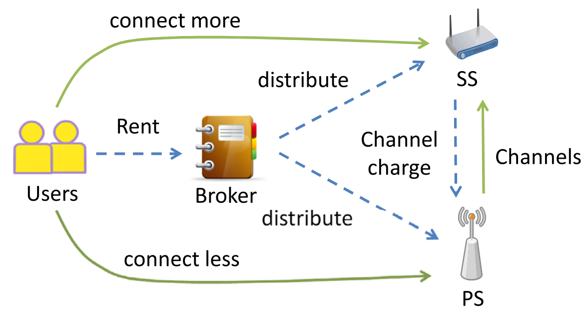

Fig. 2 Spectrum sharing network.

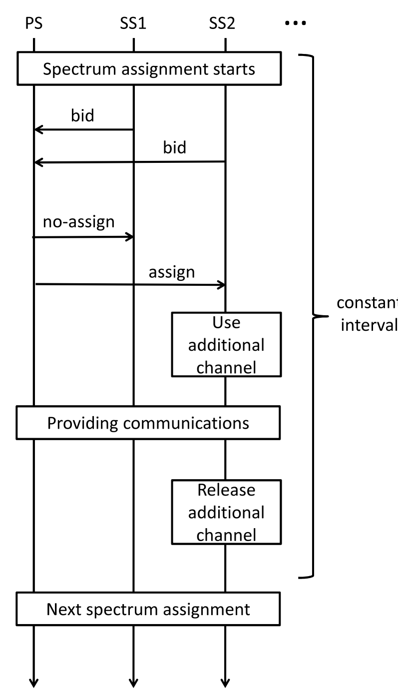

Fig. 3 Overview of the proposed method.

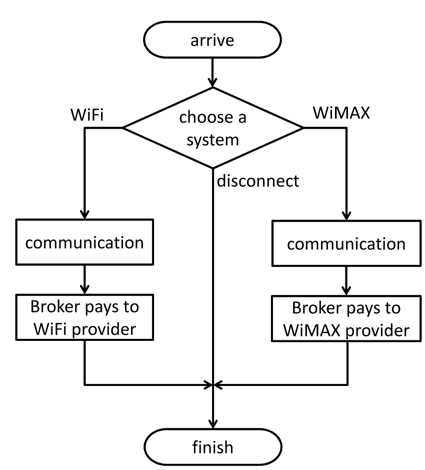

Fig. 4 Flowchart of user's behavior.

to the quantity of consumed information. In addition, the broker decides the unit price per information quantity to dispense based on total quantity. The unit price for each system should be set based on whether the system has priority for the spectrum, the extent of its coverage area, and other services used to improve QoS (Quality of Service). For this reason, typically, the unit price of the primary system will be set higher than that of secondary systems.

(3) Primary System

As shown in Fig. 3, after receiving bidding price from SS providers, PS provider decides the channel assignment to obtain higher revenue.

Because we assume spectrum property rights, the primary system cannot use a channel while lending, and thereby, decrease its throughput. The decrease will cause lower user satisfaction. In the worst case, users leave the system. To compensate for this loss, the primary system receives channel charges from secondary systems.

Specific procedures are proposed in 3.2.1.

(4) Secondary System

As shown in Fig. 3, each SS provider decides bidding price to obtain an additional channel from PS provider to attract more users.

Using the additional channels assigned by the primary system, secondary systems intend to increase the number of connected users. On the other hand, secondary systems must pay the fee associated with the channels.

Specific procedures are proposed in 3.2.2.

3.2 Spectrum Assignment

As shown in Fig. 5, a spectrum channel can be assigned to two or more secondary systems that are not adjacent to each other. The numbers of assigned channels and target access points are decided by the primary system based on prices submitted by secondary systems using the following steps.

1. Each secondary system determines the payment price.
2. A primary system searches for the optimal assignment pattern that maximizes the sum of payments offered from secondary systems without interference.
3. Based on the profit obtained from the assignment, the primary system decides the number of channels to assign.

Because system providers get more benefit via spectrum trading, they must estimate their revenue to make decisions. In other words, system providers must learn user behaviors. θ is the dominant parameter in the supposed disaggregate behavioral mode. Providers gather data of alternatives chosen by users and attributes that have an effect on user decisions, and then, estimate parameters such that they maximize the likelihood function (12).

$$L_\theta = \prod q_i, \tag{12}$$

where $i \in I$ is the chosen alternative.

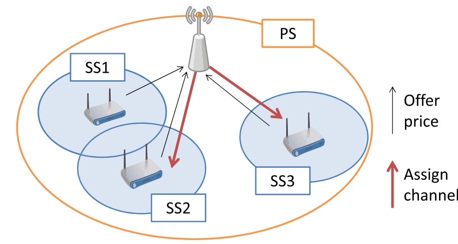

Fig. 5 Price offering and channel assignment.

3.2.1 Primary Provider's Decision: Channel Assignment

A primary system can obtain the maximum revenue $R^{(p)}(c)$, which is the sum of all rental values from the assigned secondary systems based on the number of assigned channels c. It can be obtained by using [6]. When c is given, [6] finds a spectrum assignment pattern that maximizes the total throughput. In this paper, however, we use this method to find a spectrum assignment pattern that maximizes the revenue of PS by changing the objective function. Thus, the profit of a primary system $\pi^{(p)}(c)$ is given by

$$\pi^{(p)}(c) = R^{(p)}(c) - P^{(p)}\Delta N^{(p)}(c), \tag{13}$$
$$\Delta N^{(p)}(c) = N^{(p)}(c) - N^{(p)}(0), \tag{14}$$

where $P^{(p)}$ is the unit price per request sent to the primary system by the broker and $\Delta N^{(p)}(c)$ is the estimated number of decrease in users connected to the primary system. Using the connecting probability shown in Eq. (11), the number of users who connect to the primary system is expressed as

$$N^{(p)}(c) = \tau \sum_{a\in A} \lambda_a \sum_{n_1=0}^{\infty} \sum_{n_{2j_a}=0}^{\infty} q_1(n_1, c_1, n_{2j_a}, c_{2j_a}) \cdot p_{a,n_1,n_{2j_a}}(c_1, c_{2j_a}), \tag{15}$$
$$c_1 = c^{(p)}_{INIT} - c, \tag{16}$$

where λ_a is the arrival rate of users at area a, which is as small as the secondary coverage range; A is the coverage area of WiMAX; τ is the time interval between channel assignments; $c^{(p)}_{INIT}$ is the initial number of channels of the primary system; c_{2j_a} is the number of assigned channels of the secondary system j_a in area a; and $p_{a,n_1,n_{2j_a}}$ is the ratio of the number of users in area a connected to the primary system, n_1, to that of the secondary system, n_{2j_a}.

Note that by substituting the probability q shown in Eq. (11) into Eq. (12), providers are able to predict θ based on user choice data.

For simplicity, we approximate $N^{(p)}$ over a short period τ using

$$N^{(p)}(c) = \tau \sum_{a\in A} \lambda_a q_1(n'_1, c_1, n'_{2j_a}, c_{2j_a}), \tag{17}$$

where n'_1 is the time-mean value of n_1 and n'_{2j_a} is the time-mean value of n_{2j_a}.

Finally, a primary system determines the number of assignment channels used to maximize the profit. Therefore, the value of c' is given by

$$c' = \arg\max \pi^{(p)}(c). \tag{18}$$

3.2.2 Secondary Provider's Decision: Price Setting

To ensure that a profit is achieved, a secondary system j offers price $x_j(c)$ for the cth channel, which is represented as

$$x_j(c) = \Delta R_j^{(s)}(c) \cdot (1 - \alpha_j), \tag{19}$$

$$\Delta R_j^{(s)}(c) = R_j^{(s)}(c) - R_j^{(s)}(c-1), \tag{20}$$

where $R_j^{(s)}(c)$ is the revenue of the secondary system j assigned c channels, and α_j is the net income rate of the secondary system j. Therefore, the system can achieve a profit $\pi_j^{(s)}$, which is calculated as

$$\pi_j^{(s)} = \Delta R_j^{(s)}(c)\alpha_j. \tag{21}$$

Let $N_j^{(s)}$ be the number of users connected to system j, and $P_j^{(s)}$ be the unit price per request set by the broker based on the aggregate number of requests. Then, the revenue $R_j^{(s)}(c)$ can be represented as

$$R_j^{(s)}(c) = P_j^{(s)} N_j^{(s)}(c). \tag{22}$$

Similarly to Eq. (15), the number of users connected to The secondary system j, which is assigned c channels, is given by

$$N_j^{(s)}(c) = \tau\lambda_{a_j} \sum_{n_1=0}^{\infty} \sum_{n_{2j}=0}^{\infty} q_2(n_1, c_1, n_{2j}, c_{2j}) \cdot p_{a_j,n_1,n_{2j}}(c_1, c_{2j}), \tag{23}$$

where a_j is the area of system j.

As shown in the previous section, we estimate the values of n'_1 and n'_2, which are the possible numbers of users connected to the primary and secondary system, respectively. Thus, $N_j^{(s)}$ in τ can be approximated by

$$N_j^{(s)}(c) = \tau\lambda_{a_j} q_2(n'_1, c_1, n'_{2j}, c_{2j}). \tag{24}$$

4. Performance Evaluation

4.1 Simulation Model

(1) Network Topology

Figure 6 shows the network model of the WiMAX/WiFi integrated network used in this simulation. One WiMAX base station (BS) and 10×10 = 100 small areas are allocated in the access area of the WiMAX system. The WiFi access points (APs) were allocated to the small areas based on the *distribution rate*. For example, if the distribution rate is 0.75, 100×0.75 = 75 small areas are selected at random, and each area has a WiFi AP.

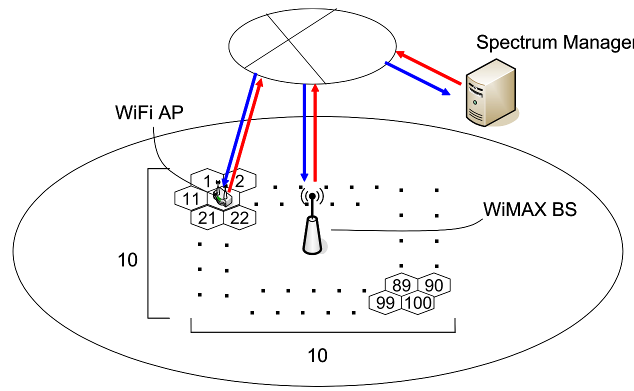

Fig. 6 Simulation model.

The spectrum of the WiMAX BS was divided into several channels with widths of 20 MHz. The WiMAX system was assumed to provide 40 Mbps per channel, in accordance with [26]. The WiFi systems were assumed to provide 17.5 Mbps per channel, according to our preliminary experiments using NS2 [27]. Additionally, the spectrum utilization, the load status of each system, the control of the spectrum assignment, and implementation of the GA were managed by Spectrum Manager, as shown in Fig. 6.

(2) Traffic Model

In this paper, we focus on the best-effort traffic such as data downloading or web browsing. Users were asked to download a file with a size of 10 MB. When a new mobile user subscribed to the sharing network arrived, the user decided whether to connect to a wireless system or not based on the disaggregate behavioral model. When downloading completed, the mobile user left.

We assume that traffic calls occurred following a Poisson arrival process, and that the arrival rate depended on the existence of the WiFi AP. Generally speaking, because WiFi APs are installed in locations in which people gather (e.g., cafes, offices, and train stations), we set the call arrival rate in an area with a WiFi AP at w times higher than that in an area without WiFi AP. Therefore, let λ_a be the arrival rate of an area with WiFi AP. The arrival rate of an area without WiFi is set to λ_a/w. The arrival rate λ_{all} in the entire network in this case is based on the arrival rate ratio w and the arrival rate λ_a with WiFi as follows:

$$\lambda_{all} = (\#\,of\ areas)(1-r)\frac{\lambda_a}{w} + r\lambda_a \tag{25}$$

By assuming that secondary systems are homogeneous, the unit price of secondary system j can be given by $P_j^{(s)} = P^{(s)}$. For simplicity, the net income rate α_j is set to $\alpha_j = \alpha$. Generally speaking, because of the priority of the primary system in the sharing spectrum, the broker in Fig. 2 sets the unit price of the primary y times higher than that of the secondary (y≥ 1). This situation can be represent by

$$P^{(p)} = yP^{(s)}. \tag{26}$$

To predict user behaviors, providers gather data regarding alternatives chosen by users; the expected communication time per bit is represented as t for their selections. Let c_{MAX} be the maximum number of assignment channels. Because taking the data in various conditions of the expected time increases accuracy, we assume that the number of data units is z and that half of the data are obtained when c_{MAX} channels are assigned. The other half are gathered when no channel is assigned, such that the data is diverse.

(3) Compared Methods

To make a comparison with our method, we introduced the existing method [6], called the cooperative method, as it is referred to in 2.2. To improve the average throughput in the entire network, the existing method decides the number of assignment channels that minimizes the entire network load, as shown in Eq. (27), and performs assignment.

$$\frac{\sum_{i=1}^{n} \frac{1}{\frac{c_i}{u_i}} \times u_i + \frac{1}{\frac{C}{U}} \times U}{\sum_{i=1}^{n} u_i + U} \tag{27}$$

Here, C denotes the WiMAX capacity, U is the number of users who connect to WiMAX, and n indicates the number of areas. c_i is the capacity of the WiFi AP and u_i is the number of connected users, both of which exist in area i.

Note that, as we mentioned in 2.2, existing methods [18]–[20] assume a pay-as-you-go-based charging system, so that we cannot compare with them in the right ballpark.

(4) Performance Measures

For the performance measurement, we defined the *average download time* of the entire system and the *coefficient of variance* of user download time. In this simulation, smaller *average download times* indicate a higher throughput.

(5) Parameters

We changed the following parameters and evaluated the proposed method.

- Parameters of the network model
  - Arrival rate in an area with a WiFi AP λ_a (in 1/s)
  - Distribution rate r of WiFi APs
  - Arrival rate ratio w between areas with and without a WiFi AP
  - Coefficient of the disaggregate behavioral model $\theta(= \theta_1 = \theta_2)$
- Parameters of the spectrum assignment
  - Unit price ratio between providers y
  - Net income rate of secondary systems α

The following parameters were fixed.

- Parameters of the network model
  - Initial number of channels of the primary system $c^{(p)}_{INIT} = 5$
  - Maximum number of assignment channels $c_{MAX} = 4$
  - Initial number of channels of secondary system $c^{(s)}_{INIT} = 1$
  - Bandwidth of a channel = 20 MHz
- Parameters of the spectrum assignment
  - Interval time of the spectrum allocation $\tau = 60$ s
  - Number of data units for the assumed parameter of disaggregate behavioral model $z = 2040$

The simulation was executed until one day of simulation time had passed. This simulation trial was repeated five times and the average outputs were calculated.

Table 1 shows the default settings.

Table 1 Default simulation parameters.

Arrival rate of the area with WiFi AP λ_a	0.4
Distribution rate of WiFi APs r	0.5
Arrival rate ratio x	10
Coefficient of disaggregate behavioral model θ	−4
Unit price ratio between providers y	1.5
Net income rate of secondary systems α	0.1

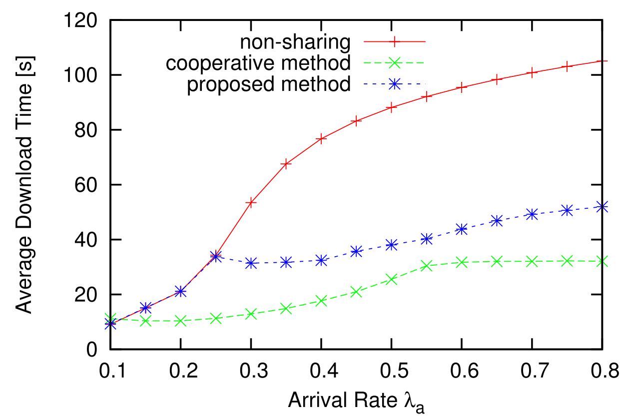

Fig. 7 Average download time.

4.2 Simulation Results

4.2.1 Basic Performance

Figure 7 and Fig. 8 show the average download time and the number of assignment channels as a function of the arrival rate λ_a, respectively. The parameter θ', which is estimated by each system, was $\theta'_1 = -4.02$ and $\theta'_2 = -4.08$. Figure 7 and Fig. 8 indicate that the cooperative method and the proposed method improve the average download time, as compared with the non-sharing method, based on effective spectrum sharing. With lower arrival rate (less than 0.3), spectrum sharing is not needed, so that the proposed method works as well as the non-sharing method.

Figure 9 and Fig. 10 show the revenue of the primary system and the average revenue of the secondary systems as a function of the arrival rate. From these figures, the revenue

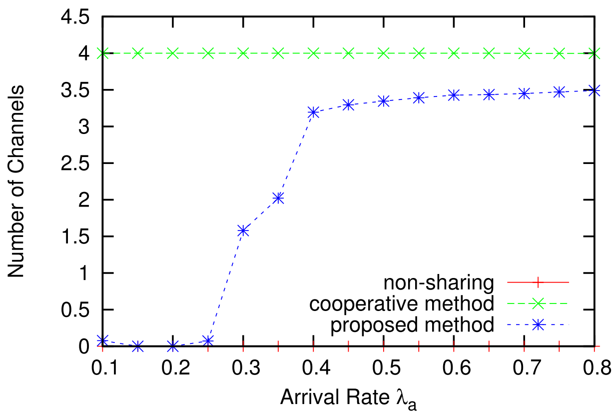

Fig. 8 Average number of assignment channels.

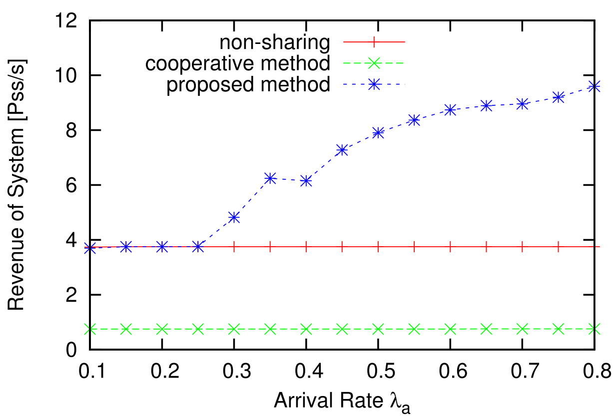

Fig. 9 Revenue of WiMAX.

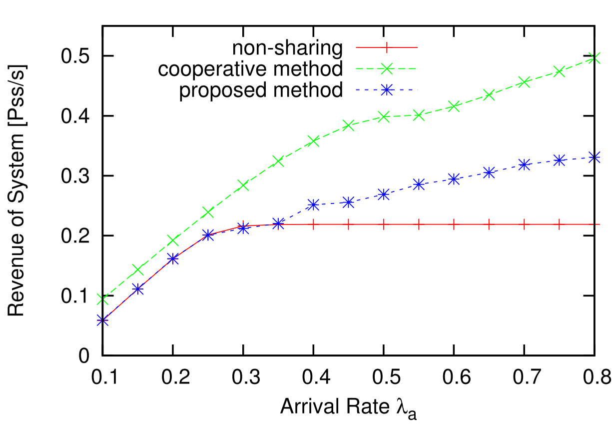

Fig. 10 Revenue of WiFi.

of both systems in the proposed method is higher than that of the non-sharing method.

On the other hand, in cooperative method, SS providers can use additional spectrum assigned from PS with no rental fee, so that they obtain the highest revenue as shown in Fig. 10. But, the revenue of PS is lower than that of the non-sharing method as shown in 9. Therefore, we conclude that this method is not practical.

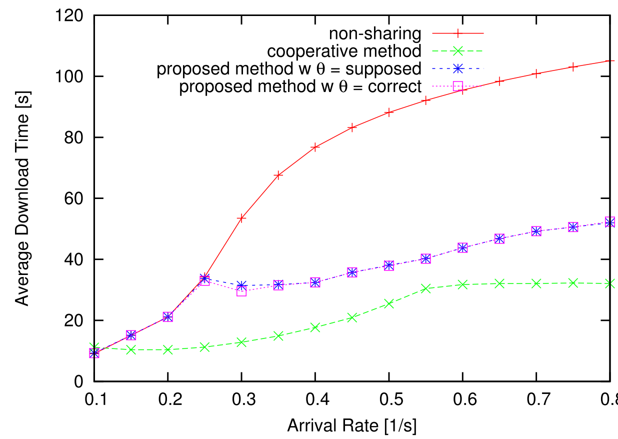

Fig. 11 Average download time ($\theta = -4$).

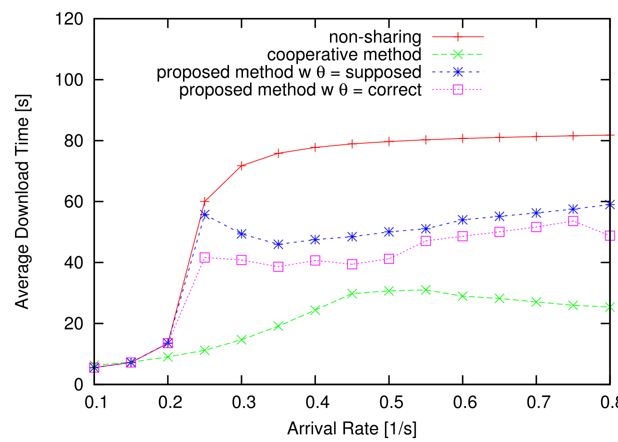

Fig. 12 Average download time ($\theta = -80$).

4.2.2 Performance Characteristic for Different Parameters of the Disaggregated Behavioral Model

Figure 11 and Fig. 12 show the average download time as a function of the arrival rate for $\theta = -4$ and $\theta = -80$, respectively. In these figures, the proposed method has two lines: one is the result when systems set θ to the correct value, and the other is the value estimated using the proposed method. When the correct θ value is -80, the supposed parameter θ' was $(-23.369, -23.0)$. Figure 11 and Fig. 12 indicates that the proposed method decreases the average download time relative to the non-sharing method in both situations with the correct value of θ and the assumed value of θ. From Fig. 12, when θ is -80, the download time of the proposed method with the correct parameters is lower than that of the method with the assumed parameters.

Figure 13, Fig. 14, Fig. 15, and Fig. 16 show the revenue of the primary system and The secondary system as a function of arrival rate. Figures 13 and 15 set θ to -4. Figures 14 and 16 set θ to -80. These figures show that the revenue of the proposed method is higher than that of the non-sharing method.

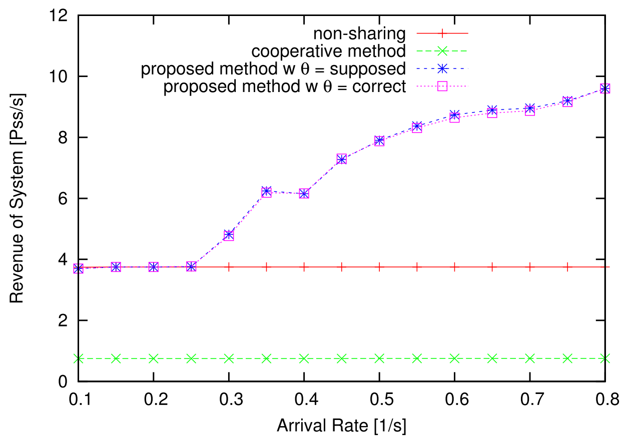

Fig. 13 Revenue of WiMAX ($\theta = -4$).

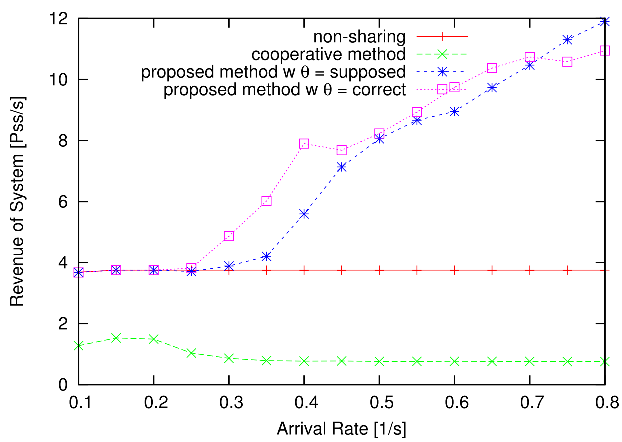

Fig. 14 Revenue of WiMAX ($\theta = -80$).

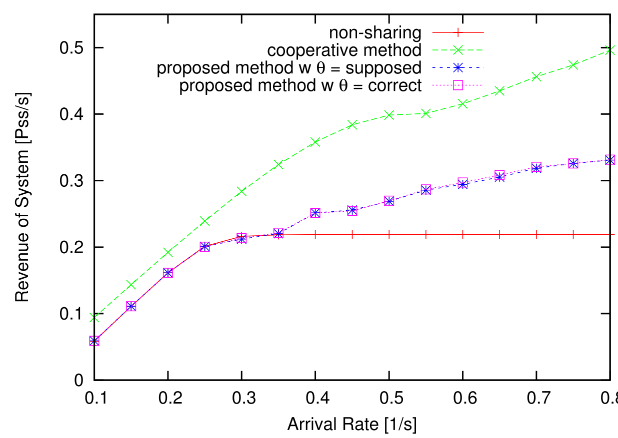

Fig. 15 Revenue of WiFi ($\theta = -4$).

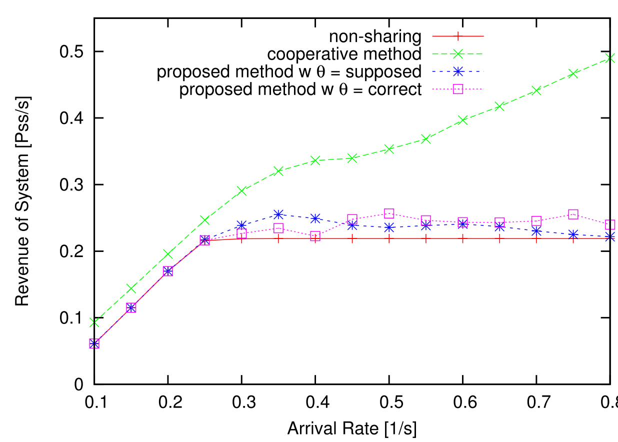

Fig. 16 Revenue of WiFi ($\theta = -80$).

Note that, in the proposed method, spectrum assignment is changed in a constant interval τ. Therefore, although the proposed method with the correct θ decided the optimal assignment at the beginning of τ, the assignment might not be optimal in the latter half of τ. As a result, in some cases, the proposed method with the correct value had less revenue than the proposed method with the supposed value. We conclude that the proposed method is no less efficient since it achieves smaller download time and higher revenue of both WiMAX and WiFi regardless of whether θ is estimated or correct. It is a future work to overcome this situation.

4.2.3 Effect of Other Parameters

We also evaluated the effect of other parameters. We summarize the results as follows.

When the distribution rate r was larger, i.e. there were more WiFi access points, more channels were assigned since primary system were able to receive fee from more secondary systems. In $0.4 \leq r \leq 0.7$, the proposed method always achieved smaller download time and higher revenue than the non-sharing method.

When arrival rate ratio x was larger, more users gathered in smaller areas. In $5 \leq x \leq 10$, the proposed method always achieved smaller download time and higher revenue than the non-sharing method.

When the unit price ratio y was higher, less channels were assigned since the primary provider set a high value on the connected users. In $1.2 \leq y \leq 2.1$, the proposed method always achieved smaller download time and higher revenue than the non-sharing method.

When the net income rate α was higher, less channels were assigned since the secondary provider set the channel prices so lower that primary provider hesitated to assign additional channels. In $0.1 \leq \alpha \leq 0.4$, the proposed method always achieved smaller download time and higher revenue than the non-sharing method.

5. Conclusions

This paper focused on efficient spectrum use to overcome the recent congestion of mobile networks and proposed a new scheme for spectrum sharing. The proposed method consists of network providers of primary systems, network providers of secondary systems, and a broker. This paper also proposed a reasonable decision strategy for providers. Simulation results showed that the proposed method achieves both higher throughput and maximum provider profits.

In future work, we will consider user mobility and handover.

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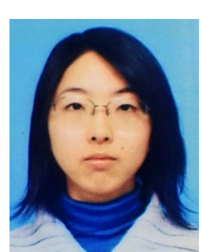
Kazuhiko Kinoshita was born in Osaka, Japan, on June 13, 1973. He received the B.E., M.E. and Ph.D. degrees in information systems engineering from Osaka University, Osaka, Japan, in 1996, 1997 and 2003, respectively. From April 1998 to March 2002, he was an Assistant Professor at the Department of Information Systems Engineering, Graduate School of Engineering, Osaka University. From April 2002 to March 2008, he was an Assistant Professor at the Department of Information Networking, Graduate School of Information Science and Technology, Osaka University. From April 2008 to January 2015, he was an Associate Professor at the same University. Since February 2015, he has been a Professor at Tokushima University. His research interests include mobile networks, network management, and agent communications. Dr. Kinoshita is a member of IEEE.



Yukika Maruyama received his bachelor's degree in engineering and master's degree in information science and technology from Osaka University, Osaka, Japan, in 2013 and 2015, respectively. Her research interests include mobile networks and spectrum sharing.

Keita Kawano received his B.E., M.E., and Ph.D. degrees from Osaka University, Osaka, Japan, in 2000, 2002, and 2004, respectively. From October 2004 to March 2010, he was an Assistant Professor of the Information Technology Center, Okayama University, Okayama, Japan. From April 2010 to March 2011, he was an Assistant Professor of the Center for Information Technology and Management, Okayama University. Since April 2011, he has been an Associate Professor of the same center. His research interests include mobile communication networks and distributed systems. He is a member of IEEE and IPSJ.

Takashi Watanabe is a Professor of Graduate School of Information Science and Technology, Osaka University, Japan. He received his B.E., M.E. and Ph.D. degrees from Osaka University, Japan, in 1982, 1984 and 1987, respectively. He joined Faculty of Engineering, Tokushima University as an assistant professor in 1987 and moved to Faculty of Engineering, Shizuoka University in 1990. He was a visiting researcher at University of California, Irvine from 1995 through 1996. He has served on many program committees for networking conferences, IEEE, ACM, IPSJ (Information Processing Society of Japan), IEICE (The Institute of Electronics, Information and Communication Engineers, Japan). His research interests include wireless networking, mobile networking, ad hoc networks, sensor networks, ubiquitous networks, intelligent transport systems, specially MAC and routing. He is a member of IEEE, IEEE Communications Society, IEEE Computer Society as well as IPSJ and IEICE.