The development of a user-centric QoE-based geo-database for spectrum markets

FORTH-ICS TR 422, JULY 2011

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***Abstract*—This paper presents the u-map, a novel user-centric geo-database for spectrum markets that enables clients to upload information about their profile, their QoE feedback for a service, traffic demand, network/spectrum conditions (e.g., interference, coverage), providers, and their position (e.g., GPS-based measurements) in a spatio-temporal geo-database. For the evaluation of this database/system, it designs a framework that integrates models of the channel, client and network operator (provider) paradigms, wireless infrastructures, types of interaction, and price adaptation. It also provides a modular simulation environment that implements this framework and enables researchers to instantiate and assess various spectrum markets. The paper analyzes the evolution of a cellular-based market that uses the u-map and shows how it can improve the network operator selection process.**

I. Introduction

As spectrum markets evolve, various mechanisms that improve the wireless access and new business-driven service paradigms (e.g., subleasing mechanisms and various coalitions among providers) have been explored. We envision a novel system that enables client devices to upload information about their usage profile, their QoE feedback for a service, traffic demand, network/spectrum conditions (e.g., interference, coverage), their network operators (e.g., base stations), and their position (e.g., GPS-based measurements) in a spatio-temporal geo-database. The profile of a client is characterized by its willingness to pay for a certain service (access or data rate), the user preference with respect to a data-rate over price (e.g., “bargain finder” users, users with relaxed price constraints but high demand for data rate), and the device power transmission constraints. QoE-based feedback correspond to ratings (or opinion scores) about the QoE of their calls and status information about their calls/flows (e.g., whether these calls were terminated successfully or abruptly or even were blocked). The traffic demand information includes a characterization of the type of service/flows, call/flow duration, and disconnection time. In this paper, we will use the words flow and call interchangeably. The information about a provider consists information about the financial cost for a call (for time-rechargeable card users that select an operator on a per call basis), the subscription rate (for subscribers), and BS/network-related information (e.g., base stations that were accessed). Most of this information is recorded by the user device and corresponds to a certain time period. Information such as the QoE feedback can be provided *explicitly by the user* (e.g., as in the case of Skype calls) or estimated using an algorithm. Initially, each device maintains this information locally.We call the system that runs on a client device *u-map* client and the recorded user information, the u-map trace.

This database expands in a user-centric fashion, as the actual uploading of the u-map trace to a server can take place in regular basis, e.g., at the end of a day or a month (parameter that a client device can configure). Such systems can be beneficial to regulators, clients, and operators: One of the primary role of regulators is to ensure a social welfareness, a fair, inclusive treatment of the various user populations with respect to the services and access, e.g., by minimizing the number of disconnected customers. Clients target to improve their access (e.g., by reducing their blocking probability) and satisfy their demand, according to their profile. The u-map can be accessed by other users in order to obtain information about a network provider, its coverage, price, quality of services, and its customers satisfaction and make an educated selection. Clients may use statistics provided in this map to select a network operator. Providers also access this database to obtain information about their coverage, user feedback and user population in order to improve/adjust their deployment, their dimensioning/capacity planning, services, e.g., detecting hot spots or “dead spots” (i.e., areas of weak coverage). Providers can use the collected statistics (e.g., user characteristics, requirements and populations), to instantiate/model their market in order to determine the prices, understand the customer population, evaluate “offline” various services and strategies. Also, they can use the collected statistics (e.g., about user characteristics, requirements and populations), to instantiate the market in the modelling framework/simulation platform and analyze its evolution. The u-map can be developed using various paradigms: either as a grass-root/community-driven effort or as a regional or governmental-based effort for the benefit of citizens/consumers/public sector, or even as a business-driven service (e.g., with subscription for certain type of queries and free/open for other type of information).

Recently, databases have been proposed to maintain spectrum/physical-layer based information ([1], [7]). Unlike these database approaches that focus on spectrum availability/usage, “whitespace”, and physical-layer data, the u-map integrates a richer service- and “market”- driven set of information. To the best of our knowledge, there are no studies that propose such spatio-temporal data repositories and assess their potential impact on the evolution of spectrum markets. There is an extensive research on game-theoretical analysis of spectrum markets (e.g. [8], [6], [4], [11]). In traditional game-theoretical approaches on spectrum markets, often the utility function of providers was assumed to be known, an unrealistic and hard assumption. On the other hand, the presence of information about the quality of services of various operators is beneficial in many ways. Thus, the u-map aims to "bridge" this gap.

The u-map consists of a distributed system of u-map servers and clients. u-map traces are stored locally at the smartphone device and are uploaded regularly at the server. A u-map server maintains data for each of its clients. It also runs the following operations: (a) communicates with umap client devices, authenticates them, and allows them to upload their u-map traces, (b) processes, sanitizes the newly uploaded data (e.g., detect malicious, misconfigured devices, synchronization issues, duplicate entries), and verifies their accuracy (e.g., detects inconsistencies), (c) updates its records with the newly received and verified client data, (d) authenticates umap clients that submit spatio-temporal database queries on the data and responds to these queries, (d) builds various geo maps that visualize the data. Furthermore, the u-map servers need to ensure data integrity and fault-tolerance, detect malicious and misconfigured users, perform non-repudiation, and protect user privacy.

The development of the u-map triggers several interesting issues related to systems (e.g., scalability of the system, privacy assurance, performance), statistical analysis (e.g., type of data to be stored, their spatio-temporal scale, validation processes), and network economics. However, due to the space constraints, we will only focus on a preliminary performance analysis of the concept via simulations. Specifically, to illustrate how the u-map can be used, we formed a game-theoretical framework of a spectrum market, which consists of providers and clients: Providers and clients are agents that sell/sublease and buy spectral resources, respectively. Updating mechanisms are chosen to model their learning and decision mechanisms and choice of utilities, spatial structure and (stochastic) updating mechanisms define completely a multi-agent evolutionary game. We developed a simulation platform that implements this framework and analyzed the evolution of the most typical spectrum provision paradigm, a cellular-based market (in Section II). In the context of this market, we proposed different access paradigms (e.g., subscribers and rechargeable card users) and a novel price adaptation algorithm. This paper builds on our earlier work [3]. This work introduced the game-theoretical framework and simulation platform, without however considering a diverse set of users (subscribers vs. card users) and the u-map. Section III analyzes the evolution of this market under different client populations and information availability (e.g., u-map) scenarios. Finally, Section IV summarizes our main findings and future work plans.

II. MODELING FRAMEWORK AND SIMULATION PLATFORM

The modelling framework is parameterized based on the channel, infrastructure and network topology, type of users (e.g., requirements, demand, mobility, profile), providers (e.g., access protocol, price adaptation mechanism), and their interactions, client/provider distributions, mobility, and available information. The simulation environment based on this framework is modular, in that, it can instantiate and implement different models for these parameters. For example, the channel can be modeled using large-scale propagation models (e.g., path-loss and shadowing) and small-scale models (e.g., multipath fading).

Providers This work considers the cellular topologies of two providers, owners of spectral resources, that offer wireless access via their BSs to clients in a small city. Furthermore, we assume that the providers divide their channels into time-frequency slots according to a TDMA scheme.

Pricing To penalize an aggressive increase of the transmission power, the providers adopt a pricing scheme that charges the clients proportionally to the transmission power they invest.

Dynamics of providers The dynamics in related game-theoretical approaches typically consider a well-defined model of the payoff of each provider, which is used to perform the price adaptation. This is a strong and unrealistic assumption, which we will relax. Specifically, we propose a novel price determination/adaptation algorithm which assumes that providers know *only* their own prices and the prices of their competitors and measure their own revenue. That is, we assume that providers do *not* a priori know the utility that corresponds to a price they may offer in the market. Let us introduce now this new dynamics:

Polynomial-based approximation of payoff A provider performs a novel price adaptation algorithm based on a *second-degree concave polynomial* approximation of the payoff function and estimates its parameters based on its own history of the game evolution. This approximation is simple yet appropriate to capture the mathematical properties of the payoff function of a provider. Specifically, each provider keeps track of the last combinations of prices that have been offered as well as the corresponding values of its revenue. It periodically fits the polynomial to the recently collected data by solving a least-square problem with the additional constraint that the polynomial is concave, formulated as a *semi-definite program*. The price is adapted by "moving towards" the direction of the partial derivative of the polynomial that corresponds to that specific provider and with a certain step. Providers adapt their prices at time instances generated via a stochastic process (for example Poisson distribution). Furthermore, notice that in models used frequently in related game-theoretical approaches (e.g., Gibbs sampler, metropolis), agents (e.g., clients) choose strategies at times generated by a Poisson process. In contrast, in this dynamics, agents may consider different distributions.

Channel To simulate the channel quality, we employed the

Okumura Hata path-loss model for small cities. Moreover, the contribution of shadowing (expressed in dB) to the channel gain at the positions of BSs follows a multivariate Gaussian distribution with mean $\mathbf{0}$ and a covariance matrix that considers the shadowing effects [5] and BSs positions. To model the effect of angular correlation of shadowing, we "represent" each BS using six points, located on a circle with center the BS position. When a client communicates with a specific BS, the contribution of shadowing to the channel gain is equal to the value that corresponds to the point representing the BS, whose direction is the closest to the direction of arrival of the signal [2].

The interference power at a BS during a time frequency slot is computed considering the contribution of all interfering devices at cochannel BSs. Moreover, cochannel BSs of the same provider may not be synchronized, resulting in "overlapping" time frequency slots, and thus, in devices that cause interference during more than one slots.

Client populations Two types of client populations are present: the *card users* and the *subscribers*. A card user selects a BS at the start of each call *dynamically*, while *subscribers* choose their provider upon their arrival in the region and connect *only* to BSs of *that provider for the remaining duration of the experiment*. Note that while the subscription is a traditional service in cellular networks, the card usage paradigm is novel and can be realized by the technological advances in cognitive radios.

Clients have two competing objectives, namely, to maximize the achievable transmission rate and to minimize the financial cost to achieve this transmission rate. The transmission rate is computed based on the Shannon capacity theorem, although more sophisticated models that take into consideration the modulation schemes can also be incorporated easily [9]. A client is characterized by a *price-tolerance* threshold and a *target transmission rate* threshold. Based on their preference, clients can also be distinguished in two categories, namely the *price-preference* and *transmission rate-preference* ones. In rate preference, clients aim to optimize *only their transmission rate* when selecting a BS, given that this BS can satisfy *both* the price tolerance and target transmission rate thresholds. Clients with price preference aim to minimize the financial cost of acquiring a time-frequency slot, when selecting a BS, given that this BS can satisfy *both* the price-tolerance and target-transmission rate thresholds. Note that this utility function assumes that the client aims to remain always connected as long as its criteria (on price and target rate thresholds) are satisfied. Only if any of the thresholds are not satisfied, the client chooses to remain disconnected

Client demand Clients generate requests to connect to a BS (i.e., *calls*). The duration of calls and disconnection periods are given by appropriate stochastic processes.

Client mobility Clients move with pedestrian speed. The position of a client at the end of a disconnection period is chosen randomly from a circular region with center the position of the client at the beginning of the disconnection and radius the maximum possible travelled distance during this period. If a client ends up in a position outside the borders of the city it is reflected back in the city. The simulation platform can be extended to consider other mobility models (e.g., vehicular mobility) and mobility traces.

u-map The u-map is a data structure that corresponds to a grid-based representation of a region. Each cell of the grid stores statistics about the providers and the QoE of calls. In the context of this analysis, we assume that the cell size corresponds to the simulated small city. At the end of a call, a card client reports the number of available time-frequency slots of the closest BS of each provider. Subscribers also report the number of available time-frequency slots of the closest BS of their providers. This information is uploaded and stored in a centralized database (u-map). Based on this information, the average *spectrum availability* i.e., number of available time-frequency slots of a BS of a provider, averaged over all collected measurements, is computed. Subscribers select the provider with the highest average spectrum availability. In this paper, the main purpose of the u-map is to reduce the call blocking probability. In a more general context, different type (e.g., QoE-based) of measurements can be recorded on the u-map, the cell size of the u-map may vary, and different BS/provider selection mechanisms can be employed to improve the QoE of a user.

III. Performance evaluation

Wireless network infrastructure The simulation platform considers a small city, represented by a grid of 11 Km x 9 Km. Each provider has a cellular network that consists of 49 BSs placed on the sites of a triangular grid, with a distance between two neighboring sites of 1.6 Km. Moreover, each provider owns bandwidth of 5.6 MHz, that is divided into 28 channels of 0.2 MHz width. These channels are allocated to BSs according to a frequency reuse scheme with spatial reuse factors of 4 and 7, for Provider 1 and Provider 2, respectively. The closest BSs at the same frequency band as a given BS in a topology with a spatial reuse factor of 4 can be located by "moving" two steps towards any direction on the grid. On the other hand, in a topology with a spatial reuse factor of 7, by "moving" two steps towards any direction, then turning by 60 degrees, and "moving" one more step, the closest BSs at the same frequency band as a given BS can be located. This is illustrated in Fig. 1. Each channel is further divided into three time-frequency slots in a TDMA scheme, resulting in 21 time-frequency slots per BS of Provider 1 and 12 slots per BS of Provider 2. Note that a single time-frequency slot of a given BS can be offered to only one client. Also, the demand of each client is *exactly one slot*.

We consider two different BS deployments, namely, the *uniform deployment*, in which the network of each provider covers the entire city, and the *non-uniform deployment*, in which six BSs (out of 49) of provider 2 are removed. Clients located in the neighborhood of the removed BSs can buy spectral resources only from the provider 1. This is an example of a partial monopoly, in the sense that there are regions in which clients have only the option of connecting to BSs of a single provider.

Providers use the polynomial-based approximation of their payoff function to determine the prices for card clients dynamically, at time instances generated by a Poisson process with a mean rate 0.002 renewals per minute. We assume that both providers offer the same prices to subscribers, which remain fixed through the entire duration of the experiment. This is a reasonable assumption, given the time duration (30500 minutes or 21 days) and scale of these experiments. Moreover, the maximum allowable transmission power that a client can invest is 2 Watts.

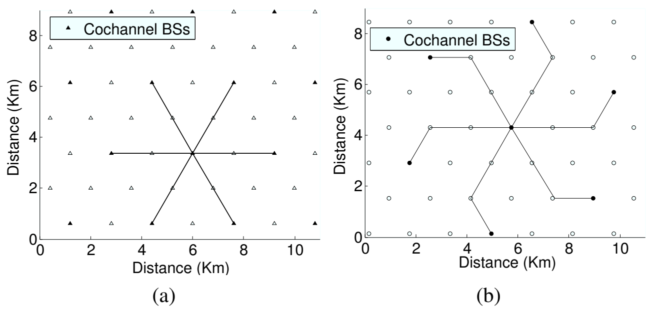

Fig. 1: Closest BSs using the same frequency band when the spatial reuse factor is 4 (left plot) and 7 (right plot).

Client populations There are 5000 clients in total (4400 card users and 600 subscribers), distributed according to a uniform distribution in the simulated region of this small city. In our experiments, the price tolerance threshold (in euros per minute) and target transmission rate (in Mbps) follow a Gaussian distribution. Specifically, we simulated client populations with *normal price tolerance* ($m = 0.15$, $\sigma = 0.0375$) and *high price tolerance* ($m = 0.2$, $\sigma = 0.0375$). We also simulated client populations with a *normal target transmission rate* ($m = 0.1$, $\sigma = 0.01$) and *high target transmission rate* ($m = 0.2$, $\sigma = 0.01$).

Client demand A client generates a sequence of call requests. The call duration follows a Pareto distribution ($x_s = 3.89$, $a = 4.5$) of mean 5min, while the disconnection period follows a Log-normal distribution ($m = 3.22$, $\sigma = 0.37$) of mean 27min. We assume that during disconnection periods, clients move with pedestrian speed of maximum value 1 m/sec, while they remain stationary during calls. Furthermore, during a call, the client remains connected at the same BS for the entire duration of the call. Fig. 2 shows a snapshot of the network topology. Specifically, it represents the BS deployment and all clients with a call at that particular time instance.

Region of interest To avoid the effect of boundary conditions, each provider takes into consideration only the interactions between BSs and clients located in a small rectangular region, corresponding to the center of the city (marked as "region of interest", the inner rectangle shown in Fig. 2). The region of interest includes 9 BSs of each provider. In the non-uniform BS deployment (*partial monopoly*), two BSs of

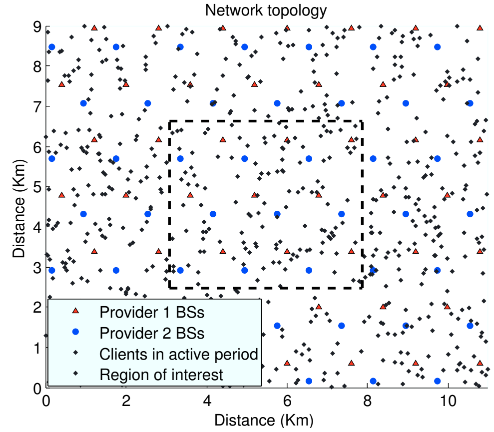

Fig. 2: A snapshot of the network topology.

the provider 2 are removed from the region of interest and four BSs are removed from the remaining area. *Only* the BSs located in that region and calls originated from that region are considered in the price adaptation algorithm.

Metrics This analysis will evaluate the impact of client characteristics and preferences, BS distribution (presence of partial monopoly) on the performance of providers and clients. The performance of a provider is characterized by its revenue and spectrum utilization while the performance of a client is indicated by the percentage of blocked calls. The *revenue* of a provider corresponds to the average total revenue of all BSs in the region of interest that belong to that provider, averaged over all Monte-Carlo runs. The *spectrum utilization* of a BS corresponds to the average percentage of time frequency slots allocated to clients. The *spectrum utilization* of a provider corresponds to the average utilization of all its BSs in the region of interest, averaged over all Monte-Carlo runs. The *percentage of blocked calls of a client* is the ratio of its successful calls over the total number of call requests. Our reported results are average statistics over all clients.

We implemented the simulation platform and this market in Matlab. 10 Monte Carlo runs were performed for each scenario (shown in Table I). Each scenario simulates a *homogeneous* client population with respect to preference and thresholds. Specifically, "P" scenarios correspond to a price-preference population, while "R" scenarios to a rate preference ones. For each scenario in Table I, we simulated two client populations, one with price-preference (P) and another with rate-preference (R) (Fig. 3). Note that in partial monopoly (rnd) scenarios, subscribers select randomly their provider. Each run represents the evolution of the market in the microscopic layer and lasts 30500 minutes (including a warm up period of 500 min). Compared to clients, the decision making and updating times of providers occur in longer time scales. The relatively long duration of our simulations is required in order to better observe the evolution of providers and their interaction with clients in this simulated small-city environment.

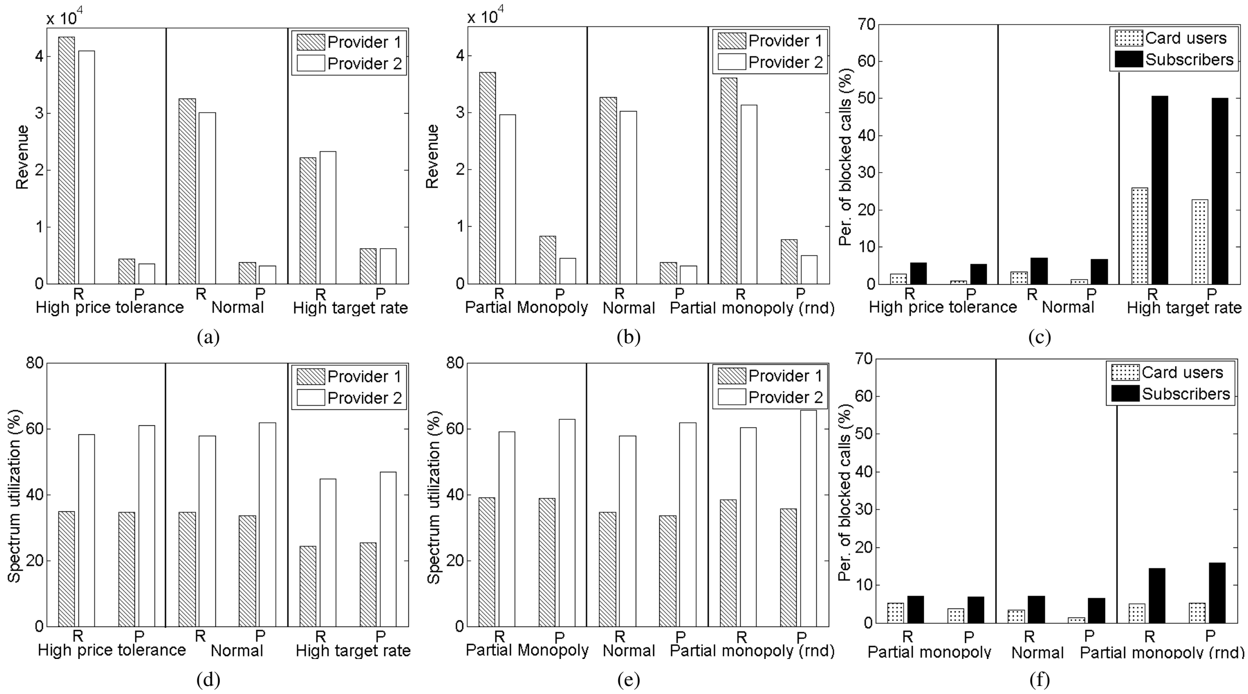

Fig. 3: Main results for a cellular-based market. Providers: Revenue (a) and (b). Spectrum utilization (d) and (e). Clients: Percentage of blocked calls (c) and (f). Averages over 10 simulation experiments, each lasting 30500 min.

TABLE I: **Description of Scenarios**

Scenario	**Price threshold**	**Rate threshold**	**BS deployment**	**u-map used**
Normal	normal	normal	uniform	yes
High price tolerance	high	normal	uniform	yes
High target rate	normal	high	uniform	yes
Partial monopoly	normal	normal	non-uniform	yes
Partial monopoly (rnd)	normal	normal	non-uniform	no

A. Analysis

In general, price preference (P) triggers a more intense competition among providers than rate preference (R). This results in relatively lower prices: fewer users will be blocked due to their price tolerance threshold (Fig. 3 (c)&(f)). Furthermore, in rate preference (R), the revenue is much larger (an order of magnitude) than in price preference (P), in which the competition between providers forces them to keep their prices relatively low (Fig. 3 (a)&(b)). In rate preference, clients tend to buy with a price equal to their maximum price tolerance threshold (in order to increase their transmission rate), while in price preference, clients are more conservative (in that they aim at paying the minimum possible price to achieve the targeted transmission rate). We observed similar trends in scenarios with stationary users that are always "on call" (with a continuous demand for access that lasts during the entire simulation). These results have been omitted due to lack of space.

In the case of increased target rate, as expected, the blocking probability also increases (Fig. 3 (c)). Interestingly, in rate preference, the revenue of providers will decrease. This is due to the fact that, although in rate preference scenarios, clients invest their *maximum transmission power that satisfies the price threshold* in order to achieve the highest possible data rate, for high target rates, fewer clients will achieve their target rate, and therefore, the blocking probability will increase, resulting to a smaller revenue and spectrum utilization.

In price preference scenarios, clients select the least expensive BS (if any) that satisfies their rate and price constraints. As the target rate increases, the price-based selection criterion "deteriorates", since a client will tend to select more frequently the BS that is "closest" to it (i.e., BS with the best channel quality) than the least expensive one (compared to lower target rate scenarios) in order to satisfy the increased data rate requirement. This allows providers to increase their prices, and thus, their revenue. (Fig. 3 (a)). Note that as the target rate increases in price preference scenarios, the BS selection mechanism exhibits more similarities as in rate preference scenarios (i.e., clients tend to choose the BS with the best channel quality). As observed also in rate-preference, the blocking probability is increased, which results to smaller spectrum utilization.

In rate preference, as the price threshold increases, we would expect that the blocking probability decreases, while the spectrum utilization also increases (Fig. 3 (c) and (d)). Interestingly, these changes are small, due to the inter-dependency of the price tolerance threshold of clients and price setting mechanism of providers. The increase of price tolerance threshold allows providers to increase their prices even further.

The increase of prices is directly reflected on the increased revenue of providers. Although the blocking probability and spectrum utilization have not changed, the prices are now higher.

As a result of the relatively higher prices in rate preference compared to price preference, the blocking probabilities are larger. Note that this is true only for card users. For subscribers, the prices are the same in both scenarios and remain fixed for the entire duration of the experiment. In addition, in price preference, the higher the price tolerance threshold, the lower the blocking probability.

Card clients have smaller blocking probability than subscribers, since on average, a subscriber is further away from the "best" BS than a card client. This is because a subscriber "belongs" to a provider, and thus, selects a BS from the set of BSs deployed by that provider, while a card client may select a BS from a larger set of BSs that belong to various providers.

In general, provider 1 has a higher spectrum availability (i.e., larger number of time frequency slots) resulting in larger revenue compared to provider 2 and smaller spectrum utilization. Moreover, this is even more prominent in the partial monopoly case, in which the difference in the spectrum availability of the two providers is increased.

In partial monopoly, unlike the case of rate preference, in which the revenue increase is not dramatic, in price preference, the revenue of the monopoly provider is doubled. This is due to the price tolerance threshold and the competition with the other provider (shown in Fig. 3 (b)). Actually, the price-tolerance-threshold is the dominant factor, given that in rate preference, the impact of competition is less prominent since clients select the BS with the best channel quality (and not the lowest price). Note that in monopoly scenarios, there are some regions in which BSs of both providers are present, resulting in a competition. In the region of monopoly, the price setting mechanism of the provider is constrained by the price tolerance threshold, while in the remaining regions, by mainly the competition among providers. The larger the region of a monopoly, the larger the flexibility for that monopoly (provider) to set its price. The competition between providers in the other regions and the tendency of the monopoly provider to increase its price give the opportunity to the other provider to also increase its price, and thus, its revenue. This is an example of cases where partial monopolies provide opportunities to non-monopoly providers to increase their revenue.

The u-map indicates that the spectrum availability of provider 1 exceeds the spectrum availability of provider 2. As expected, all subscribers select the provider 1. To evaluate the impact of the u-map, we employ a baseline scenario in which subscribers select a provider randomly (rnd). Compared to the random selection (rnd), the map-based selection exhibits lower average blocking probability for subscribers, both in rate and price preference (Fig. 3 (f)). Clearly the u-map is beneficial to clients. Potentially providers could also take advantage from the reported information about the call arrivals and distributions and user price tolerance threshold. For example, an increased blocking probability in certain areas may alarm providers for further investigation and better capacity planning. In this study, the price adaptation algorithm of providers does not employ any information about clients. It is important to note that the integration of additional knowledge about the population may further improve the performance of the price adaptation mechanism by satisfying the price tolerance threshold of a larger client population. The u-map can provide the information that the more traditional, game-theoretical dynamics require (e.g., well-defined payoff functions for providers). Even more importantly, a network operator could use information collected from such databases to instantiate a market and analyze its evolution.

IV. Conclusions and future work

The paper presented the u-map as well as a game-theoretical framework that can instantiate spectrum markets to analyze their evolution, and a modular simulation platform that implements this framework. The paper implemented and evaluated a duopoly cellular-based market, with two customer types, namely the subscribers and card users. It showed that the u-map can be beneficial in enabling subscribers to select in a more "educated" manner their network operator and improve their access. The u-map concept is powerful in that it enables providers and clients to estimate or forecast some critical information in order to improve their targets. A part of our future work is to focus on the impact of various customer types/profiles on spectrum markets. The proposed framework and simulation platform can be extended to instantiate different network and cooperation paradigms (e.g., cellular operators with spectrum subleasing services, primary/secondary spectrum markets, mesh networks). The incorporation of malicious, mis-configured or non-rational entities can be easily modeled and implemented in the simulation platform. A part of our ongoing activity is the development of a prototype that implements the main functionality of the u-map for IEEE802.11-enabled smart-phones. Building on our earlier work on VoIP [10], we will statistically-analyze the u-map traces to assess how accurate predictions and evaluations can be performed.

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