A novel multi-layer framework for modeling the evolution of spectrum markets and cognitive-radio devices

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***Abstract*—This work presents a novel multi-layer modelling framework for the evolution of spectrum markets of multiple spectrum/network operators that provide wireless access to users. It integrates models of the channel, mobility, user preference, network operators (providers), infrastructure deployment, user distribution, and price-adaptation mechanisms. Providers aim to maximize their own profit, while clients decide based on criteria, such as the financial cost of the access, transmission rate, and required transmission power. This paper gives a brief description of the modelling framework and a novel price-adaptation algorithm for providers. It presents how this framework can be used to instantiate a cellular-based market in a small city. Finally, it analyzes the evolution of this market under different topologies and user profiles, summarizing the main performance results.**

I. Introduction

Cognitive radio networks (CRNs), an emerging disruptive technology, aims to improve spectrum utilization, enabling dynamic spectrum use. This research focuses on the design of a complete *multi-layer* modelling framework of CRNs, incorporating both systems and business aspects using statistical mechanics, game theory and economics. It integrates models about the channel, network operators, infrastructure, and primary and secondary devices (e.g., their preference, constraints, placement). A distinct prominent feature is its emphasis on the interactions among the CRNs entities that occur in *multiple time and spatial scales*. The multi-layer modelling aspect is inspired by the approach in [1]. We are in the process of developing a modular simulation environment that implements the modelling framework and instantiates various models, allowing comparative assessments of spectrum-sharing mechanisms under different scenarios. The framework should enable researchers to capture different types of *information sharing*, interactions, negotiation strategies, and *trust* among entities.

To the best of our knowledge, it is the only modelling framework that attempts to incorporate such an extensive set of parameters that allow the modelling of various complex interactions of CRNs entities and business-driven cases in a realistic manner. Most of the related approaches focus on a specific sub-problem/aspect of CRNs omitting their inherent features. Specifically, they can be classified into two categories, namely, the *microscopic-* and the *macroscopic-* level ones. The microscopic-level approaches consider interactions among secondary devices at a very fine spatial level, mostly assuming a limited number of primary devices due to the high computational complexity [2], [3], [4], [5], [6], [7], [8]. On the other hand, the macroscopic approaches focus on the revenue of the providers, considering only an "average" (over large temporal or spatial scales) behavior of secondary devices [9], [10], [11], [12]. Unlike these approaches, this framework models the interactions of primary and secondary entities at *several spatial scales*, from large metropolitan areas to small neighborhoods (e.g., within the coverage of a wireless access point), enabling the instantiation of various parameters at *different time granularities*. For example, the rate at which primary devices change their prices for their spectral resources is often smaller than the rate at which secondary devices demand for spectral resources.

An intuitive way to think of the multi-layer aspect of this framework is as a set of mathematical transformations that allows to "scale up or down" the modelling environment. At the microscopic level of the framework, the various entities are modeled in fine temporal and spatial detail. On the other hand, the mesoscopic level exhibits various *aggregations*. For example, the users are modeled as a *population* with certain attributes, computed as *spatial averages* of the characteristics of the individual users of that population. Furthermore, the selection process of these user populations are no longer deterministic but *stochastic* and *location-dependent*. Due to the heterogeneity of these populations, the framework allows the definition of mixed strategies for the spectrum access negotiation process. For example, in the case of a population of users, a mixed strategy indicates the probability with which

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users choose to buy spectrum from various providers at a specific location. Section II describes the modelling framework. Section III illustrates how this framework can be used to instantiate and assess a spectrum market with cellular-based network access. Finally, it discusses our findings.

II. Modelling framework

The most important parameters of the modelling framework are (a) the channel, (b) the network topology (e.g., cellular, mesh, vehicular), (c) the network operator infrastructure deployment/distribution, (d) the user mobility and distribution, (e) the relations and interactions among primary and secondary entities (e.g., among primary devices, between primary and secondary devices, among network operators), (f) the multiple spatio-temporal scales (over which these relations and interactions are manifested), (g) the type, reliability and amount of information that is available to various entities, (h) the user preferences and tolerance criteria with respect to the wireless access (e.g., based on transmission rate, energy, financial cost, handoffs frequency, duration of disconnection) and the network operator selection mechanism, (i) the user profile (e.g., misconfigured/selfish/malicious entities), (j) the utility function of the primary entities (e.g., spectrum owner), and (k) price-adaptation algorithm.

The simulation environment based on this framework is modular, in that, it can instantiate and implement different models for the aforementioned 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., multi-path fading).

This work considers the cellular topologies of two network operators that offer wireless access via their base stations (BSs) to wireless users in a small city. The network operators (called also *providers*) are the primary entities that own a part of the spectrum, offering wireless access via their base stations (BSs). Secondary entities (called also *users*) buy the wireless Internet access from network operators for a certain duration. Furthermore, we assume that the providers divide their channels into time-frequency slots according to a TDMA scheme and each user requests a single slot for his access.

To simulate the channel quality, we employed the *Okumura Hata* path-loss model for small cities [13]. 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 covariance matrix defined in Eq. (1).

$$C(i,j) = \begin{cases} \sigma_s^2 & \text{if } i = j, \\ \sigma_s^2 e^{-\|L_i - L_j\|/X_c} & \text{if } i \neq j, \end{cases} \tag{1}$$

where σ_s is the standard deviation of shadowing (2.5 dB in our simulations), X_c is the correlation distance within which the shadowing effects are correlated [14], and L_i, L_j are the positions of the BSs i and j, respectively.

To model the effect of angular correlation of shadowing, we represent each BS with six points instead of one located on a circle with center the BS position. When a user 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 [15].

The interference power at a time-frequency slot belonging to a specific BS is computed by measuring the contribution of all interfering devices at co-channel BSs. Moreover, co-channel 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. In real wireless networks, the amount of interference at the available time-frequency slots and the channel gain will be measured by the network interfaces of BSs and sent to the users with appropriate messages. To penalize an aggressive increase of the transmission power, the providers adopt a pricing scheme that charges the users proportionally to the transmission power they invest. Moreover, the maximum allowable transmission power that a user can invest is 2 Watts.

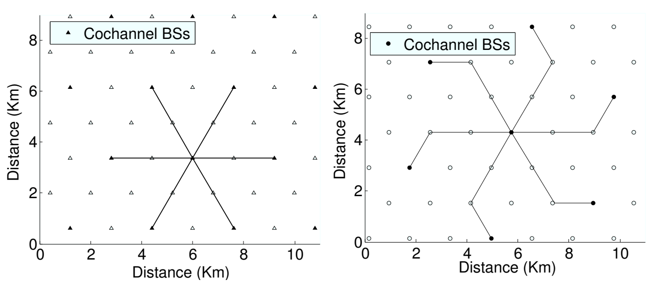
In general, different service paradigms can be modeled (e.g., *"time/recharge" cards* or *subscription-based* schemes). Most of the related approaches consider a given (*a priori* known) function that models the demand of secondary users to perform the price adaptation or decide about the amount of spectrum, which they will offer in a given market [9], [10], [11], [12]. Unlike them, this work does not assume that the demand is known and considers different algorithms for the price adaptation. Specifically, it considers that the providers only know their own prices and the prices of their competitors and measure their own revenue. No knowledge is available about the user characteristics and preferences.

The providers perform a novel price adaptation algorithm based on a *second-degree concave polynomial* approximation of the payoff function and estimate its parameters based on the 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 revenue. It periodically fits the polynomial to the recently collected data by solving a least-squares problem with the additional constraint that the polynomial is concave, formulated as a semi-definite program [16]. 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. The algorithm is described in detail in [17]. Finally, the providers adapt their prices at time instances generated via a stochastic process (e.g., Poisson distribution).

III. Performance Evaluation

A. Description of scenarios

Two cellular networks, deployed by different providers, offer services to users in a small city, represented as a rectangle of 11 Km x 9 Km. Each network 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 can be offered to only one user. Also, the demand of each user is exactly one slot.



(a) (b)

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

There is a distribution of 600 users in this region interested in buying wireless Internet access from these two providers. Each user is characterized by a *price-tolerance* threshold (i.e., he can tolerate a maximum cost for the Internet access) given by a Gaussian distribution ($m = 0.15$, $\sigma = 0.0374$) and has a *target transmission rate* (expressed in Mbps) that follows a Gaussian distribution ($m = 0.1$, $\sigma = 0.01$).

A Uniform and a Zipf topology are simulated. In the Uniform topology, users are distributed in the entire region according to a Uniform distribution, while in the Zipf topology (shown in Fig. 2), users are placed mostly at the center of the city. In both cases, users are stationary.

To avoid the effect of boundary conditions, we analyzed only the measurements that correspond to BSs and users in a small rectangular region at the center of the city (marked as "region of interest", the inner rectangle shown in Fig. 2). Specifically, *only* the BSs located in that region and users of that region that also access the Internet via those BSs are considered in the price adaptation algorithm and in the reported evaluation results. The region of interest includes 9 BSs of each provider. 150 users are present in the Uniform topology and 242 users in the Zipf topology, respectively.

Two user-preference metrics were simulated, namely the *transmission-rate* and *price-preference* ones. In rate preference, users take into consideration *only* the achievable transmission rate, given that the offered price from the specific

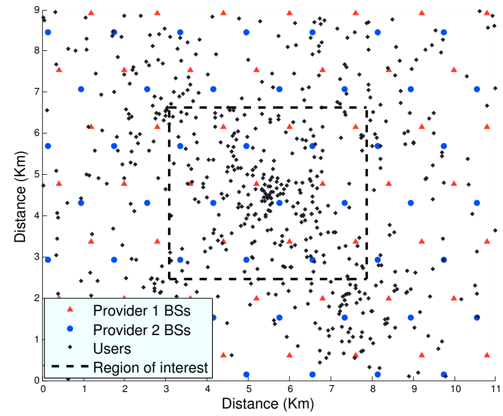


Fig. 2: Zipf-like distribution of users in a small city.

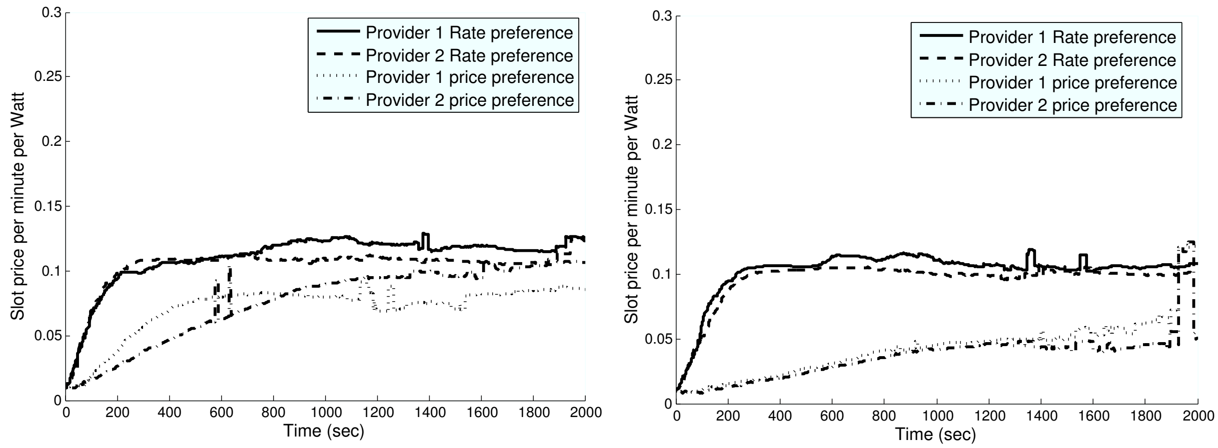
BS does not exceed their price-tolerance threshold. Users with price preference aim to minimize the cost of acquiring a time-frequency slot, given that their target transmission rate requirement is satisfied. Each user reconsiders its choice periodically (here, every 2 sec), while each provider adapts its price at time instances produced by a Poisson process with a mean of 0.03 renewals/sec. Providers run the price adaptation algorithm described in Section II. An experiment corresponds to a specific topology (The Uniform topology indicated with "U" and the Zipf topology indicated with "Z"). All the users of an experiment employ the same user preference metric (Price "P" or Rate "R" preference). It lasts for 2000 sec. The results reported for each scenario (e.g., "U-R"in Fig.4, for a Uniform topology with rate preference) are average statistics over 30 Monte Carlo runs. This simulation testbed was implemented in Matlab.

B. Simulation results and discussion

In rate-preference, a user connects to the BS that offers the best channel in terms of received SINR. Due to the spatial reuse scheme, the impact on SINR of the interference of other users at co-channel cells is relatively small compared to the channel gain, which is determined mostly by the distance between transmitter (a given user) and receiver (its BS). Therefore, users tend to select the geographically nearest BS. This has as a result providers to increase their prices, without *significantly* influencing the BS selection process of users. Consequently, the prices of the two providers converge to a relatively high value.

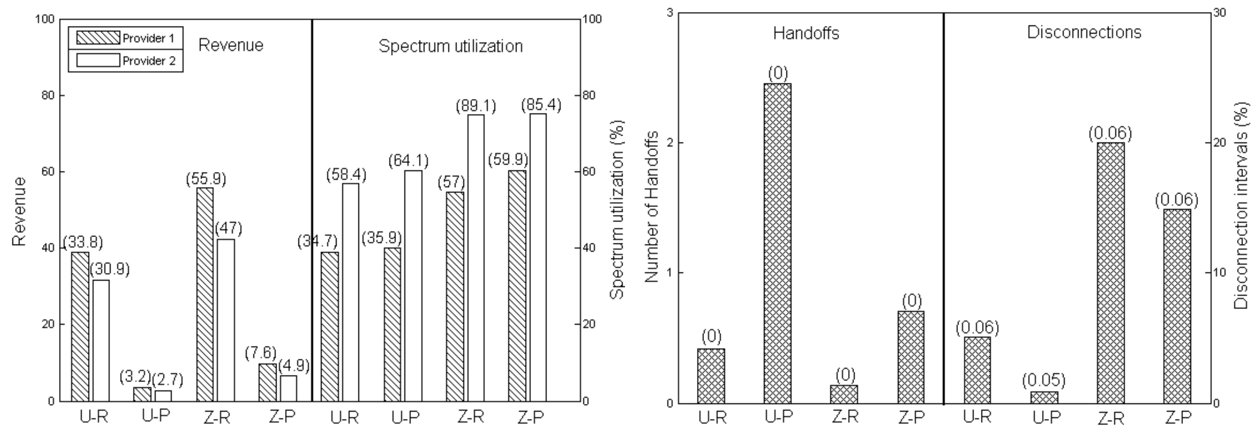
On the contrary, in price preference, users connect to a BS of the least expensive provider, given that they can still achieve their target transmission rate. In these scenarios, even small changes in the price could cause some users to change provider. This has two important implications; First, compared to the rate-preference scenario, a larger number of handoffs are performed between BSs of the two providers. Second, the intensity of competition keeps the prices of the two providers at relatively low levels.

Fig. 3 presents the evolution of prices under the two topologies and user preference metrics, while Fig. 4 summarizes the



(a) (b)

Fig. 3: (a) The price evolution in the Zipf topology, (b) The price evolution in the Uniform topology.



(a) (b)

Fig. 4: (a) Provider revenue (left) and spectrum utilization (right), (b) User handoffs (left) and disconnection intervals (right).

revenue and spectrum utilization *per BS* for each provider and the number of handoffs and percentage of disconnection of users. Specifically, the revenue corresponds to the average of the total revenue of all BS at the region of interest throughout an experiment, averaged over all Monte-Carlo runs. The spectrum utilization for a BS is the integral of the percentage of time slots assigned to users during the experiment, normalized by the duration of the experiment. The reported value is computed in the same manner as the revenue. The number of handoffs corresponds to the number of transitions between BSs of a user during an experiment, averaged over all users and all Monte-Carlo runs. The disconnection period of a user corresponds to the total percentage of time that this user is disconnected during an experiment. We compute the average over all users in an experiment, and report the average over all Monte-Carlo runs. We also indicate the corresponding median values in parenthesis.

The spatial user distribution affects the system dynamics: In the uniform topology, the total number of users located in the region of interest is 150. Furthermore, the availability of time-frequency slots of the two providers is 189 and 108, respectively. Therefore, the Provider 2 is not able to satisfy the user demand, resulting to a small advantage for the Provider 1 in terms of number of clients and revenue. On the contrary, in Zipf, in the region of interest, the user demand exceeds the availability of time-frequency slots of each provider. Thus, the providers have the opportunity to increase their prices even further, resulting in higher revenues for both providers (compared to the Uniform topology). Finally, due to the relatively high user density, the difference in the revenue of the two providers increases (compared to the revenue reported in the Uniform topology). The above results are shown in Fig.4 (a).

In price-preference, the prices are higher in the Zipf than in the Uniform topology. This is because the user demand is larger than the availability of time frequency slots of each provider. This offers more opportunities for price increase than in the uniform topology. In rate-preference, the prices in the two topologies are similar (U-R vs. Z-R), since users decide based on topological criteria. The price evolution is mostly affected by the user price tolerance threshold which follows the same distribution in both topologies.

The revenue is higher in rate-preference than in price-preference scenarios. This is due to not only the higher prices but also to the tendency of users to invest more transmission power to achieve higher rate. Finally, the spectrum utilization is higher for the Provider 2, due to its lower availability of time-frequency slots.

As observed earlier, compared to rate-preference, the price-preference corresponds to a larger number of handoffs (e.g., U-R vs. U-P, and Z-R vs. Z-P). However, exactly the opposite occurs for the disconnection intervals. In rate preference, the prices are higher than in price preference, exceeding the price tolerance thresholds of a larger number of users.

Interestingly, in the Uniform topology, a larger number of handoffs and lower disconnection periods occur. This is due to the lower user demand in the Uniform topology than in the Zipf topology (150 vs. 242 users), resulting to a larger availability of time-frequency slots. Thus, the likelihood that a user will be able to connect to a BS is higher in the Uniform topology than in the Zipf one. This means that a user has on average more opportunities to roam to a different network. On the contrary, in Zipf, the likelihood of fully-utilized time-frequency slots of BSs is higher, resulting to fewer choices for users, and thus, longer disconnection periods.

Finally, the median value of handoffs and disconnection periods is much lower that the corresponding mean values, indicating that most users are connected to a single BS for the entire experiment. A small number of users switch back and forth between BSs or remain disconnected for almost the entire duration of the experiment.

IV. Conclusions and future work

This paper presents a microscopic spatial and temporal scale of the interactions between cellular network providers and users. It analyzes the impact of topology and price and rate preference on the price evolution, provider revenue, spectrum utilization, number of handoffs and disconnection periods. It also highlights the effect of price tolerance and preference on the degree of competition between providers. It is possible under different BS deployments, user distributions, population sizes, and preferences to observe phenomena like price wars and monopolies. Furthermore, it is part of future work to explore how these interactions evolve in larger spatio-temporal scales.

In this work, users select the appropriate BS (and provider) based on their current observations/measurements of the channel quality and price. A part of our on-going effort focuses on modelling other novel schemes, such as the integration of their previous measurements ("history") or available community-based measurements (collected from various devices) to enhance the network/provider selection process. Moreover, this work considers user utility functions based on the channel capacity (a measure of the maximum achievable transmission rate). However, we plan to incorporate user-centric functions that take into consideration finer-level statistics on network conditions and reflect the user satisfaction.

Another prominent feature of our research is the design and integration of spectrum-sharing mechanisms that will realize various competitive, cooperative, and hybrid business models. Such models will be instantiated using specific parameters of the proposed framework (e.g. the amount of information shared among various entities and type of interaction) and access paradigms that depict realistic business cases. For example, in a cooperative business model, cellular networks may establish long-term agreements with TV networks or network providers of IEEE802.11 infrastructures form coalitions. We believe that this work sets the directions for developing a general framework that allows researchers to instantiate, implement, and assess interesting and realistic spectrum-based market approaches.

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