A game-theoretical modeling framework and simulation platform for cellular-based access markets

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Abstract

The wireless access, use and traffic demand are on a fast rise, leading to an increased demand for radio spectrum. On the other hand, current spectrum allocation policies are highly inefficient resulting in an underutilization of this valuable natural resource. To increase spectral efficiency, the research community has proposed cognitive radios that enable new network architectures and access markets, opening new opportunities for business cases. Unlike traditional cellular-based markets, these markets have larger sizes, are more heterogeneous, and potentially can offer an improved set of services.

This thesis presents a modeling framework and simulation platform for access markets. It integrates models of the customers (e.g., preference, demand, mobility, transmission power, willingness-to-pay), channel, provider infrastructure deployment, customer distribution, and price-adaptation mechanisms. Providers aim to maximize their own profit, while clients decide based on various criteria, such as the financial cost of their access, transmission rate and required transmission power. Moreover, it introduces the “flexi-card”, a novel service paradigm that allows a user with a cognitive radio to dynamically access Base stations (BSs) of different providers based on various criteria, such as its profile, network conditions, and offered prices. Card users can select the appropriate operator and BS on a per-call basis. Customers could dynamically decide to buy a long-term subscription or become card users. This research analyzes the evolution of a duopoly that offers the flexi-card service as well as long term subscriptions, considering a diverse customer population from the perspective of customers, providers, and regulators. The analysis demonstrates

that the flexi-card substantially improves the performance of a market in terms of the percentage of disconnected users, blocking probability, and social welfare.

Περίληψη

Τις τελευταίες δεκαετίες, η ζήτηση για ασύρματη πρόσβαση ολοένα και αυξάνεται, οδηγώντας σε μία αντίστοιχη αύξηση της ζήτησης φάσματος. Από την άλλη πλευρά, οι τρέχουσες πολιτικές ανάθεσης φάσματος είναι σε μεγάλο βαθμό μη αποδοτικές, οδηγώντας σε μερική εκμετάλλευση του πολύτιμου αυτού φυσικού πόρου. Για να αυξήσει την αποτελεσματική χρήση του φάσματος, η επιστημονική κοινότητα πρότεινε τις γνωστικές ραδιοεπικοινωνίες, που εισάγουν νέους τύπους δικτυακών αρχιτεκτονικών και αγορών πρόσβασης ανοίγοντας νέες επιχειρηματικές δυνατότητες. Σε αντίθεση με τις παραδοσιακές αγορές των κυψελωτών δικτύων, αυτοί οι νέοι τύποι αγορών έχουν μεγαλύτερα μεγέθη, είναι πιο ετερογενείς και μπορούν να παρέχουν καλύτερες υπηρεσίες.

Αυτή η μεταπτυχιακή εργασία παρουσιάζει μία μεθοδολογία μοντελοποίησης και μία πλατφόρμα προσομοιώσεων για αγορές πρόσβασης. Περιλαμβάνει μοντέλα για τους πελάτες (προτιμήσεις, ζήτηση, κίνηση, ισχύ εκπομπής, ανοχή στην τιμή), το κανάλι, τη δικτυακή υποδομή των παρόχων, την χωρική κατανομή των χρηστών και το μηχανισμό αναπροσαρμογής των τιμών. Οι πάροχοι σκοπεύουν στη μεγιστοποίηση του κέρδους τους, ενώ οι χρήστες αποφασίζουν με βάση διάφορα κριτήρια, όπως το κόστος πρόσβασης, το ρυθμό μετάδοσης και την απαιτούμενη ισχύ εκπομπής. Επιπλέον προτείνει την ¨ευέλικτη κάρτα¨, μία υπηρεσία που επιτρέπει σε χρήστες που διαθέτουν το κατάλληλο υλικό και λογισμικό, να συνδέονται δυναμικά σε σταθμούς βάσης διαφορετικών παρόχων με βάση διάφορα κριτήρια, όπως το προφίλ τους, την κατάσταση του δικτύου και τις προσφερόμενες τιμές. Πελάτες που χρησιμοποιούν την ευέλικτη κάρτα μπορούν να επιλέγουν τον τηλεπικοινωνιακό τους πάροχο ανά κλήση. Αυτή η εργασία αναλύει την εξέλιξη μίας δυοπωλιακής αγοράς που

προσφέρει την υπηρεσία της ευέλικτης κάρτας καθώς και συμβόλαια μεγάλης διάρκειας, θεωρώντας ένα ετερογενή πληθυσμό χρηστών και εξετάζοντας την επίδοση της αγοράς από την σκοπιά των χρηστών, των παρόχων και των ρυθμιστών φάσματος. Η ανάλυση αναδεικνύει ότι η ευέλικτη κάρτα βελτιώνει την επίδοση μίας αγοράς και συγκεκριμένα μειώνει το ποσοστό των αποσυνδεδεμένων χρηστών και την πιθανότητα απόρριψης κλήσεων ενώ αυξάνει την κοινωνική ευημερία.

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To my family

Στην οικογένεια μου

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Chapter 1

Introduction

The wireless access, use and traffic demand are on a fast rise, leading to an increased demand for radio spectrum. According to forecasts, by 2014, the mobile data traffic will exceed the 3.6 exabytes per month worldwide. Besides performance reasons, the efficient spectrum utilization is imperative from an economic point of view: spectrum is a scarce resource of high economic value (its worldwide value is approximately 1 trillion USD) for both the society and the wireless industry with a wide variety of active business stakeholders. Shannon's law sets the limits on the achievable transmission rate. To increase the spectral efficiency, the research community has been developing multiple input multiple output (MIMO) systems, intelligent and directional antennas, channel assignment and topology control protocols, and improved MAC protocols. Another direction is cognitive radio networks (CRNs), an emerging disruptive technology, which aims to improve spectrum utilization, by enabling dynamic spectrum use by devices capable of sensing the spectrum and detecting currently idle spectrum holes, and using them without introducing interference to licensed, primary users [1].

The expectation that the commercial deployment of CRNs will lead to improved network services and accelerate the evolution of wireless technologies has triggered numerous research and industrial activities, such as the opportunistic radio access to specific dedicated bands and the extension of the unlicensed part of the spectrum. However, telecommunication operators and cellular providers are reluctant to follow this paradigm shift. The cognitive radio technology empowers networked devices with new degrees of flexibility and freedom, enabling new network architectures, access methods, and services, enriching the roles of service providers, and opening new opportunities for businesses cases. This important paradigm shift can be demonstrated by examples from the area of spectrum markets and wireless access services.

1.1 Motivation

Until recently, the main spectrum market was the one of traditional cellular-based providers with Base station (BS) deployments and long-term licenses to fixed predetermined channels with exclusive access rights. However now new spectrum market paradigms arise: (a) network operators that deploy femtocell or mesh-like wireless networks dynamically, opportunistically, in a self-organizing manner based on the expected traffic demand in a region, creating secondary spectrum markets, (b) virtual (or service) providers that "sublease" certain part of the spectrum dynamically for certain time periods and in specific regions from (traditional) cellular providers, forming "local spot markets", and (c) assuming an "open (free) spectrum", network operators may deploy Base stations (BSs) in certain regions and perform with new-comer operators a joint channel allocation. Major research and economic interest stems from these potentially large spectrum markets. For example, a company in US, SpecEx, has been already providing an online marketplace of available licensed radio spectrum for sale or lease on the secondary market by enabling someone to search for spectrum offerings and access underused spectrum.

This paradigm shift becomes accentuated by the multi-dimensional convergence in telecommunications, e.g., in mobile, fixed and broadcasting, in voice and data, in wireless and cellular networks, in ad hoc and infrastructure-based networks and in spectrum use as well as by the grass-root and cooperative aspects that have also characterized the Internet evolution. The paradigm of an unlicensed spectrum with different types of providers that offer dynamically wireless Internet access also reinforces the development of novel grass-root, cooperative communication paradigms and services. Owners may deploy services or rent/lease spectrum assets, while service providers need not be spectrum owners. They may create coalitions, e.g., by sharing a part of the infrastructure, spectrum or information about their customers. However how such markets should be designed in order to be profitable and efficient? What are the important business-aspects that need to be considered with respect to price determination, operational and service models, types of coalitions, user requirements and demand? How and when should a service provider decide to expand its deployment of BSs? What would be the appropriate service models to offer under certain spectrum conditions and presence of competition? Such questions motivate this research. Unlike the traditional cellular-based markets, these spectrum markets have larger sizes (in terms of number of potential providers), are more heterogeneous (in terms of services, clients, and providers), and potentially can offer an improved set of services (e.g., higher multiplexing gains and a reduction of costs due to the higher utilization of existing infrastructure). The space under which such markets need to be analyzed is multi-dimensional and tightly integrates systems and business aspects. We believe that business-driven comparative analysis studies of the evolution of spectrum markets based on different spectrum access/sharing paradigms are crucial in assessing the benefits of CRNs and further accelerating the technology transfer. The main objective of this research is to set the foundations for the development of a modular modeling framework and simulation platform that enables the business-driven comparative analysis study of various spectrum markets and services under a diverse set of customer profiles and performance metrics.

1.2 Challenges

Unlike the traditional cellular-based markets, the new types of spectrum markets have larger sizes (not only in terms of the number of clients but also of potential providers), are more heterogeneous (in terms of services, clients, providers, and network architecture), multi-layered (in the spatial and temporal granularities in which different phenomena manifest), more dynamic (e.g., in the decision making process of clients and providers, network deployment, channel allocation), multi-dimensional (many parameters, such as the spectrum allocation, BS deployments, and pricing, affect their evolution and performance), and are more complex (e.g., the interplay of various parameters affect their performance). To the best of our knowledge, there is no framework modeling spectrum markets that has addressed all these issues. From a systems perspective, the aforementioned characteristics impose several performance consequences, such as an increased algorithmic and computational complexity. To analyze the evolution of such markets, the aforementioned mechanisms and interactions among entities need to be modeled at the appropriate time (which may vary from seconds to years) and spatial scales (ranging from a few meters to the size of a country). The modeling and simulation of such markets in fine-detail (i.e., at the microscopic-level, considering each entity and interaction) results in an extremely large number of events, generated by their entities and their interactions. It can be very computational expensive to keep track of all the details and not amenable to analysis. Moreover, it is difficult to design proper adaptation mechanisms for providers (e.g., price setting, capacity planning, spectrum acquisition) and users (e.g., service selection) due to the interplay of various parameters at different spatial and temporal scales which may introduce feedback loops that can make the market unstable. From a modeling perspective, it is unclear how such complex, dynamic and large-scale markets can be modeled in an accurate, robust, and scalable manner. Even appropriate theoretical methodologies that would enable the analysis of the accuracy and scalability tradeoffs for different modeling approaches have not been yet proposed.

1.3 Contributions

This master thesis makes the following contributions:

1. It develops a modeling framework and simulation platform that allows us to instantiate and assess various types of cellular-based access markets. This framework contains models for (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 providers and users, (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) and the provider selection mechanism, (i) the utility functions of the providers, and (j) 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.

2. It introduces the u-map, a novel system with a user-centric geo-database that enables users to upload measurements that their devices collect about network conditions, interference, and coverage as well as their feedback about their profile and quality of experience (QoE) for certain types of services. This database will be generated in a grass-root fashion and can be accessed by users to make an educated selection of the operator/service as well as by providers to obtain information about the customer profiles/market and experience in order to improve/adjust their deployment, services, and prices. The vision behind such databases, like the u-map, is to assist towards the "self-regulation" spectrum environment, reducing the need for active spectrum compliance testing, and as a consequence, making time for other regulator activities.

3. It proposes a novel service for cellular networks, the "flexi-card": A flexi-card client is not associated with a specific operator but can dynamically access BSs of different operators based on various criteria, such as its profile, the network conditions, and the offered prices, on a per-call basis. Such service is a typical access paradigm in wireless local area networks (LANs) and similar to the concept of "soft" (or virtual) subscriber identity module (SIM) cards. We show that the flexi-card becomes a catalyst in a cellular-based market, providing significant benefits, compared to traditional markets with only subscribers. For example, the analysis demonstrated that a duopoly that offers the flexi-card in addition to subscriptions alleviates the market exclusion effects, dramatically reduces the percentage of disconnected users, decreases substantially the blocking probabilities, and improves the social welfare!

4. It evaluates the performance of cellular-based spectrum markets considering different customer populations and the perspective of regulators, users, and operators, possibly with conflicting objectives. A primary role of regulators is to promote competition and social welfare, a fair inclusive treatment of various user populations with respect to services and access, e.g., by minimizing the number of disconnected customers. Clients target to improve the QoE of their access under their cost constraints, while the revenue maximization is the primary objective of providers.

1.4 Roadmap

Chapter 2 presents the related work in the areas of cognitive radios and spectrum markets. First, it provides a taxonomy of approaches that design and optimize the performance of cognitive radio networks. Then, it classifies studies of spectrum markets with respect to different dimensions. First, it distinguishes between two different market layers, the "spectrum acquisition" and "service provisioning" and presents studies that model either of these layers or both of them. Then, it classifies proposed approaches into "microscopic" and "macroscopic" ones. Microscopic approaches model the market in a very fine level of detail while macroscopic approaches perform various aggregations to reduce the computational complexity. Finally, there is a discussion on the various types of price-adaptation algorithms that are used in the cognitive radio literature.

Chapter 3 describes in detail the proposed modeling framework and simulation platform. Specifically, it defines the channel model, the decision-making mechanism of users (with respect to the provider from which they buy wireless access), and introduces a novel price-adaptation algorithm for providers that is based on a second-degree concave polynomial approximation of their payoff function. It also introduces the u-map, and illustrates a case in which it can be used to reduce the blocking probability of user calls. Finally, it defines two different types of markets and performs exhaustive simulations to evaluate their performance.

Chapter 4 introduces the "flexi-card" service for cellular-based spectrum markets. It describes the decision making of users with respect to service selection (subscription or flexi-card) and BS selection (selection of a BS to perform a call).

It also describes two different price adaptation mechanisms, one for the subscription rates and one for the rate of the flexi-card service. Finally, it performs exhaustive simulations to evaluate the performance of a spectrum market that offers the flexi-card service. Chapter 5 contains the conclusions of this thesis and Chapter 6 our future work plans.

1.5 Related publications

The modeling framework and simulation platform described in Chapter 3 are the main contributions of the following publications:

1. "**A novel multi-layer framework for modeling the evolution of spectrum markets and cognitive-radio devices**", published in *IEEE DySPAN 2011* by Georgios Fortetsanakis, Markos Katsoulakis, and Maria Papadopouli.

2. "**A Game-theoretical modeling framework for spectrum markets and cognitive-radio devices**", *ICS-FORTH, Heraklion, Crete, Greece, Tech. Rep. 414, February 2011* by Georgios Fortetsanakis, Markos Katsoulakis, and Maria Papadopouli.

The concept of the "u-map" described in Chapters 3 and 4 is introduced in the following technical report: "**The development of a user-centric QoE-based geo-database for spectrum markets**", *ICS-FORTH, Heraklion, Crete, Greece, Tech. Rep. 422, July 2011* by Georgios Fortetsanakis, and Maria Papadopouli.

Finally, the "flexi-card" service described in Chapter 4 is the main contribution of the following technical report: "**To subscribe, or not to subscribe: The analysis of new service paradigms in cellular markets**", *ICS-FORTH, Heraklion, Crete, Greece, Tech. Rep. 424, July 2011* by Georgios Fortetsanakis, Maria Papadopouli, Gunnar Karlsson, Manos Dramitinos, and Emre A. Yavuz. (Submitted to IEEE Infocom 2012)

Chapter 2

Related work

2.1 Cognitive radios

During the last decades, the demand for wireless access is on a fast rise. On the other hand, current spectrum allocation policies are highly inefficient resulting in underutilization of this valuable natural resource. This motivates the design of new communication protocols and access paradigms that will increase spectrum utilization allowing the satisfaction of the increasing demand. Currently, spectrum access is defined by two different paradigms, the "exclusive use", and "spectrum commons". In exclusive use, the spectrum is owned by the government and is licensed to particular providers and application types. On the contrary, in spectrum commons the spectrum is unlicensed and can be accessed by any device that follows a specific set of rules that are part of an industry standard (e.g., IEEE 802.11).

To increase spectrum utilization, the research community introduced a new spectrum access paradigm, the hierarchical access. In this paradigm, some intelligent devices called cognitive radios are allowed to function at licensed portions of the spectrum, given that they would not affect the quality of service of the licensed systems. In particular, the total interference power that is measured at the receiver of a licensed system should not exceed a certain threshold, the interference temperature limit [2]. In some cases, it is sufficient to ensure that the probability of exceeding a certain level of interference power should be kept lower than a threshold [3].

The hierarchical access paradigm has been adopted by various schemes in the literature. These schemes try to improve the efficiency of cognitive radio networks using various techniques. For example, some of them use power control to limit the levels of interference, while others use beamforming, to restrict the transmission and reception of signals to certain directions [4, 5, 6]. Another method reduces the interference power by decoding the message of primary systems and subtracting it from the overall signal [7]. Some approaches dynamically adjust the transmission rate according to the current wireless conditions [8] while others allocate channels to the various transmitter-receiver pairs, to increase the spectral efficiency [9, 10, 11, 12, 13, 14]. The proposed channel allocation algorithms are centralized or distributed, proactive or on-demand, and they assign contiguous or non-contiguous bands to the various devices [15, 16].

Generally, the goal of all these approaches is to improve the efficiency of cognitive radio networks. They also consider different performance metrics such as, the total achievable throughput or the degree of fairness of the medium access scheme. Moreover, some approaches consider the user-perceived QoE (quality of experience) of certain types of applications, and model it in terms of various network parameters, such as the transmission rate and the packet-error probability [17, 18]. Using such metrics, the allocation of resources to the various devices can be performed more efficiently.

According to other approaches, the secondary users could dedicate a portion of their transmission power to enhance the transmissions of the primary system [19]. By using complicated coding techniques, like the dirty-paper coding, they can achieve transmission rates that are close to the channel capacity. Even though such approaches are interesting in a theoretical point of view, it is difficult to implement them in real systems. This is because the secondary users should be informed about the modulation scheme and the message of the primary system.

2.2 Spectrum market modeling

2.2.1 Market layers

In the cognitive radio literature, spectrum markets have been modeled in two different layers, the *spectrum acquisition* and *service provisioning*. Spectrum acquisition, focuses on the process with which providers acquire licenses to operate at certain portions of the spectrum, from the state or other providers. These licenses are offered in different time and space granularities, from long-term nationwide licenses to regional licences with relatively short duration. On the contrary, service provisioning describes how providers choose the types of services they will offer to end users, using the spectrum they have acquired. It also models the price determination for the offered services as well as the end-user decision making.

Several studies model the spectrum acquisition of providers, based on different assumptions. Some of them [20, 21] focus on nationwide licenses that are valid for a long period of time (e.g., ten years), while others describe secondary spectrum markets, in which license holders may sublease a portion of their spectrum to other firms, at specific regions and for shorter periods of time. For example, Niyato *et al.* [22] consider multiple primary providers that sublease a portion of their unused spectrum to a secondary provider to increase their profit. They also study a scenario [23] with multiple providers that are organized in a certain hierarchy, in which the provider i can buy spectrum from the provider $i-1$ and can sublease a portion of it to the provider $i+1$. Jia *et al.* [24] consider a license holder that subleases a porion of its unused bandwidth to a set of providers to increase its revenue, while in other studies [25, 26] multiple sellers offer spectrum to multiple buyers. All these sellers offer one channel of the same bandwidth and each buyer requests for access to a single channel. Kasbekar *et al.* [27] also proposed a framework with multiple sellers that offer spectrum to multiple buyers, but each buyer is able to win more than one bands. Moreover, two different types of licenses were considered, primary and secondary licenses. A primary license holder has the highest priority to access the spectrum while secondary license holders function in an opportunistic manner.

In service provisioning, there are also various studies with different assumptions on the types of offered services and the characteristics of end-users. For example, Wysocki *et al.* [28] consider a provider that offers two types of services, one for primary and one for secondary users. The price for the secondary service is determined in a way that balances out the QoE degradation of the primary service. Other studies [29, 30] consider service provisioning in code division multiple access (CDMA) wireless networks, in which users are charged according to the transmission power they invest, while Gao *et al.* [31] consider a provider that offers services of different quality and price. The service quality is indicated by the maximum transmission power, a user can invest. Niyato *et al.* [32] assume that multiple providers offer services to multiple groups of users. The providers decide the amount of spectrum and price they will offer to the market while users choose the provider from which they will buy services. Xing *et al.* [33] introduce a model, in which users choose provider based on their own profile that is characterized by their target QoE and willingness to pay, while Ji *et al.* [34] design an auction with multiple providers that offer channels to multiple users. Each provider offers one channel for sale that can be allocated to a single user. Finally, Chang *et al.* [35] consider a provider that offers services to both primary and secondary users and sets a limit to the number of channels that can be allocated to the secondary service to guarantee the quality of the primary service.

Except of studies that focus only on spectrum acquisition or service provisioning there are some approaches that consider both procedures jointly [36, 37]. In these approaches, multiple providers acquire spectrum from a central spectrum moderator and use it to offer services to end users. Each provider decides on the amount of spectrum to be purchased, based both on the current prices that are set by the moderator, and the user demand. Moreover, it sets the prices for the end-user services in a way that maximizes its revenue. The decision making of providers with respect to the amount of spectrum to be purchased and the price setting of services manifest in different time granularities. Specifically, a provider purchases spectrum much more rarely than it adapts the prices for the end-user services.

2.2.2 Level of detail

Spectrum markets are complex systems which involve interactions between a large number of end-users, each having its own profile, and many providers with network infrastructures of different technology, that offer various types of services. They also involve interactions between providers and spectrum regulators that set the rules for the spectrum allocation and its proper use. All these interactions manifest in different spatial and temporal scales. For example, spectrum licenses are renewed much more rarely compared to the rate with which providers change the prices for the end-user services. Similarly, end users take their decisions much more often compared to the rate with which providers change their strategies. Thus, it is difficult to design a complete model of spectrum markets that describes in detail all these interactions.

Existing models of spectrum markets can be classified into two general categories, namely, the *microscopic-* and the *macroscopic-* level ones. The microscopic-level models consider the interactions among all participating entities in a spectrum market, at a very fine level of detail, mostly assuming a limited number of such entities due to the high computational complexity. For example, in some studies [29, 30, 31, 33, 34, 35, 37], each user is modeled as a distinct entity with its own profile that may depend on its willingness to pay or its target QoE. Wysocki *et al.* [28] also propose a model which describes in detail the user arrival process in the market.

On the other hand, the macroscopic-level models consider only an "average" behavior of certain types of entities (e.g. end users) to make the analysis more tractable. For example, some studies [22, 36] use a polynomial of second degree to describe how the user demand depends on the offered prices. Others [23, 24] consider that each provider knows a priori the amount of spectrum its clients need without discussing the details of the provider-user interaction that leads to this demand. Niyato *et al.* [32] also proposed a model in which users are divided into groups and only the average behavior of users in each group is taken into consideration. Finally, there are studies [25, 26, 27], focusing on the spectrum acquisition of providers, which assume that each provider knows its valuation for the available spectrum, but they do not discuss how this valuation is determined.

Unlike the previous approaches, this thesis sets the foundations for the design of a framework that models the interactions of 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*. Moreover, it will provide the set of models and mathematical transformations that allow to "scale up or down" a modeling environment in order to analyze a certain phenomenon at the appropriate level of detail, controlling the loss of information. Specifically, models in this framework will be more detailed compared to macroscopic approaches but will perform various aggregations of entities to reduce the amount of unnecessary information. That way the computational complexity will be reduced compared to the microscopic approaches allowing the study of more complex markets.

2.3 Price adaptation

Pricing of spectral resources is an important issue in most studies of spectrum markets. In studies that model the spectrum acquisition of service providers in various spatial and temporal scales (nation-wide or regional licenses), the auctions are the preferable mechanism to perform the spectrum allocation. In the economic literature [20, 21] it is proven that auctions is the best means to allocate spectrum to firms that value it the most, thus increasing the social welfare. In studies that model the competition of providers to offer services to wireless users, various pricing algorithms have been considered. These algorithms can be classified in two general categories based on the amount of information that is available to providers. The first class of algorithms assumes that providers have full knowledge of the market, which means that they can predict the reaction of users to all possible choices of strategy they could make. Moreover, the providers know the strategies and the utility functions of all their competitors. These assumptions are strong and unrealistic in most practical scenarios, in which the information that is available to providers is limited. Thus, in the second class of algorithms the providers have partial knowledge of the market and use reinforcement learning to predict the behavior of users and their competitors.

2.3.1 Full-knowledge algorithms

The most commonly used full-knowledge price setting algorithms are (a) best response, and (b) fictitious play. In these algorithms, each provider offers a price that maximizes its expected revenue based on a suitable prediction of the behavior of its competitors.

1. *Best response* [36, 38, 39] assumes that providers take actions one after the other according to a certain ordering. When a provider acts, it changes its price in a suitable way that maximizes its performance, assuming that the environment will remain the same. Specifically, each provider chooses a price that maximizes its immediate payoff, based on the assumption that the prices of the other providers will not change. Although best response fails to account for simultaneous adaptation from multiple providers, it can be shown to converge to a Nash equilibrium in special cases, such as two-player zero-sum games, supermodular games, potential games, and certain types of submodular games.

2. *Fictitious play* [40] also considers that providers take actions one after the other according to an ordering scheme. In contrast to best response, providers choose the offered prices in a way that maximizes their expected revenue based on the assumption that the historical distribution of actions of the other providers is a good predictor of their future actions. Fictitious play is characterized by good convergence properties in practice, although converge to Nash equilibrium is known to be false in general. One drawback is the need to explicitly observe the behavior of all opponents which may be unrealistic in certain scenarios.

2.3.2 Partial-knowledge algorithms

In case that providers do not know a model of the behavior of users or other providers, they adopt various types of reinforcement-learning algorithms to predict this behavior based on data that are collected throughout the market evolution. The most common types of reinforcement-learning algorithms used in the spectrum-market literature are (a) steepest ascent, (b) stochastic learning, (c) Q-learning, (d) regret-based algorithms, and (e) the amoeba algorithm. The above algorithms are based on different types of available information to providers.

1. *Steepest ascent* [22, 32] is adopted is scenarios in which, a provider may not be able to observe the profit or the offered prices of other providers. Therefore, in order to perform the price adaptation, a provider should be based only on local information. In this case, it will adapt the price towards the direction that maximizes its profit with a certain step. Specifically, the relationship between the current and the new price is described as follows:

$$p_i(t+1) = p_i(t) + a_i \left(\frac{\partial U_i(\mathbf{p})}{\partial p_i} \right) \tag{2.1}$$

   where $p_i(t)$ is the price offered by the provider i at time t, $\mathbf{p}$ is a vector with the current prices of all providers, U_i is the utility function of the provider i, and a_i is the adjustment speed (i.e. learning rate) of the adaptation. To estimate the derivative of its utility function with respect to the price, a provider performs a small variation in the currently offered price and observes the resulting difference in the user demand. This method is based on the assumption that the spectral resources can be divided in a continuous manner among the users. However, in most practical cases of medium access schemes the spectral resources are discrete. For example, in time division multiple access (TDMA), spectrum is divided into time-frequency slots while in frequency division multiple access (FDMA), in channels of fixed bandwidth. In such cases, the estimation of the derivative of the utility function of a certain provider becomes a more complicated issue.

2. *Stochastic learning* algorithms [33] assume that providers adapt their prices in alternating turns and that they can offer a price from a given discrete set. At each turn, a provider chooses a price randomly, according to a certain probability distribution defined on the set of available prices, and measures the resulting revenue. Then it adapts the probability distribution in such a way, that increases the weight of prices that achieved high revenue and penalizes prices that achieved low revenue. For example, this can be

done by proper filtering of the probability distribution. These types of algorithms have two important disadvantages. First they are characterized by very slow convergence and for a given provider, the price adaptation of its competitors introduces a non-stationary environment.

3. *Q-learning* [38, 39] describes the environment of an agent using a Markov decision process. A finite-state Markov decision process is a tuple $< X, U, f, p >$ where X is a finite set of environment states, U is a finite set of agent actions, $f : X \times U \times X \to [0, 1]$ is the state transition probability function, and $p : X \times U \times X \to R$ is the reward function. In spectrum pricing problems, the state of the environment $x \in X$ is a vector which contains the prices of the competitors of a certain provider. When this provider performs an action $u \in U$, all its competitors will react to this action by changing the state of the environment from x_k to x_{k+1}. Then the provider receives a reward r_{k+1} according to the reward function $r = p(x_k, u_k, x_{k+1})$. The goal of the provider is to maximize at each turn, the expected discounted return:

$$R_k = E\left\{\sum_{j=0}^{\infty} \gamma^j r_{k+j+1}\right\} \tag{2.2}$$

In most practical cases of spectrum markets, the providers do not know a priori the expected discounted return that is associated with the various available prices and they estimate it based on the history of the market evolution. Specifically, each provider maintains a "lookup table" which contains an approximation of the expected discounted return $Q(x, u)$ for all possible pairs of the environmental states and provider actions. At each step of the algorithm, the provider chooses a new price based on the currently estimated lookup table and using the Boltzmann exploration strategy. Then it updates the estimation of the function $Q(x, u)$ according to a certain adaptation rule. A detailed description of single-agent and multi-agent Q-learning can be found in [41]. Various important issues arise when implementing the Q-learning algorithm in practice. It is difficult to maintain lookup tables for the function $Q(x, u)$ especially in markets with many providers due to their large size. Moreover, it is not clear how these tables should be initialized. Finally, in many cases the speed of convergence of the Q-learning algorithm is very slow.

4. *Regret-based algorithms* [40] are in a sense a generalization of fictitious play, which replace explicit opponent modeling with an implicit "regret matrix". Each player maintains such a matrix, which tracks, for every pair of actions j, k the difference in utility that a provider would have obtained if it had taken the action k in the past everywhere it took action j. Given that the current action of a provider is j, the probability of choosing action k in the next step is proportional to the regret from j to k. Learning proceeds by exploring and switching to actions that are perceived as "better" according to this regret measure. Maintenance of the regret matrix requires no explicit awareness of other providers. The main disadvantage is that providers are required to know, the utility they would have obtained for each possible choice of strategy they could have made in the past. This requirement is removed in modified regret matching that is presented in [42].

5. *The amoeba algorithm* [43] is used in a case that a provider offers n different types of services at different prices. Specifically, each provider maintains $n+1$ sets of prices and their corresponding revenue as it was recently measured in the market. The convex hull of these sets of prices is a nondegenerate simplex of n dimensions. At each iteration, new sets of prices are computed along with their corresponding values of revenue, to form a new simplex. The algorithm stops when the revenue that corresponds to the vertices of the simplex satisfies a predefined condition. One important disadvantage of this algorithm is that the price adaptation of rival providers introduces a non-stationary environment which is not taken into consideration.

In this thesis we used two different price-adaptation algorithms, that are an extension of steepest ascent and best response respectively. As mentioned earlier, steepest ascent is based on the assumption that a provider can measure the derivative of its utility with respect to the offered price by performing a small variation of the current price and measuring the user reaction. This method is valid only when the spectral resources can be continuously divided among users.

However, in this thesis we study TDMA-based cellular networks in which users can buy access to a discrete number of time-frequency slots and therefore the derivative estimation becomes a more complex issue. To overcome this problem, we assume that providers perform the price adaptation 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 sets 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 [44]. The price is adapted using the steepest ascent method on the estimated polynomial. The algorithm is described in detail in Section 3.1.3.

In best response, it is assumed that a provider has full knowledge of the user demand and the utility functions of other providers. This is a strong assumption which we relax by considering that providers only know the distribution of the user profiles and can observe only the prices that are offered by their competitors. Then we apply a clustering algorithm on the profiles of users and we represent each class of users by a single imaginary entity which we call "representative user". The demand of a representative user is computed in such a way that matches the average demand of the users it represents. Then each providers simulates off line the decision making of representative users for all prices it can offer and estimates its revenue. Finally, the provider chooses the price that maximizes its revenue based on the assumption that the prices of its competitors will remain the same. A complete description of the algorithm is provided in Section 4.1.7.

Chapter 3

The modeling framework and simulation platform

Cognitive radios, an emerging disruptive technology, aims to improve spectrum utilization and efficiency, enabling dynamic spectrum use. Unlike traditional cellular-based access markets, in which users associate with specific providers, new market types arise in which users will be able to choose their provider on a per call basis. Their choice will depend on various parameters such as their proximity to BSs of the various providers, the channel conditions, and the offered prices. These types of markets will offer more opportunities for wireless connectivity to users and will increase their QoE.

In this work, we introduce a modeling framework and simulation platform that studies cellular-based access markets with two different types of users, the subscribers, and the card users. Subscribers perform long-term contracts with a specific provider and can connect only to BSs of that provider for the entire duration of their contract. On the contrary, card users can connect to a BS belonging to any provider at the start of each call. Different pricing schemes are adopted to charge the two types of clients. Providers in this framework are competitive and they set their prices in such a way that maximizes their profit while users decide based on various criteria, such as, the financial cost of their access, the quality of the offered services, and the required transmission power.

Our modeling framework takes into consideration various parameters, such as,

(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 providers and users, (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) and the provider selection mechanism, (i) the utility functions of the providers, and (j) 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.

3.1 Modeling framework

3.1.1 Channel model

To simulate the channel quality, we employed the *Okumura Hata* path-loss model for small cities [45]. 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. (3.1).

$$C(i,j) = \begin{cases} \sigma_s^2 & \text{if } i = j, \\ \\ \sigma_s^2 e^{-\|L_i - L_j\|/X_c} & \text{if } i \neq j. \end{cases} \tag{3.1}$$

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 [46] 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. These points lie on a circle with center the BS position and radius 1m and they are equally spaced. Furthermore, we determine the value of shadowing at the points that represent all BSs by drawing a sample from the distribution described in Eq. (3.1). 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 [47].

We compute the interference power at a time-frequency slot belonging to a specific BS by measuring the contribution of all interfering users at cochannel BSs. Moreover, we assume that cochannel BSs of the same provider are not synchronized resulting in overlaps between multiple time-frequency slots and thus in users that interfere to 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.

3.1.2 User decision making

Consider that there is a set of users U in a particular geographical region. Each user $u \in U$ takes its decisions by solving the following optimization problem.

$$\begin{aligned}
\underset{\mathbf{T}_u}{\text{maximize}} \quad & \sum_{s \in S} a \left(\frac{B}{N}\right) \log_2 \left(1 + \frac{T_u(s) G(u,s)}{I(s)}\right) - bc(s) T_u(s) \\
\text{subject to} \quad & T_{min} \leq \sum_{s \in S} T_u(s) \leq T_{max} \\
& \sum_{s \in S} c(s) T_u(s) \leq C^u_{max} \\
& \sum_{s \in S} \left(\frac{B}{N}\right) \log_2 \left(1 + \frac{T_u(s) G(u,s)}{I(s)}\right) \geq R^u_{tar} \\
& \sum_{s \in S} sign(T_u(s)) = 1
\end{aligned} \tag{3.2}$$

Where S is the set of available time-frequency slots at neighboring BSs, $G(u,s)$ is the channel gain that the user u observes at the time-frequency slot s, and $I(s)$, $c(s)$ are the interference plus noise power and monetary cost of the slot s respectively. B is the width of a single channel and N is the number of time-frequency slots in which a channel is divided. Furthermore, T_{min}, T_{max}, C^u_{max}, and R^u_{tar} are the minimum and maximum allowable transmission power, the maximum price per minute that the user u can tolerate for a time-frequency slot and the target transmission rate of the user u. Finally, the vector $\mathbf{T}_u = (T_u(s))_{s\in S}$ contains the transmission power that the user u invests in all available time-frequency slots and the function $sign(x)$ is defined as follows.

$$sign(x) = \begin{cases} 1 & \text{if } x > 0, \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

The objective of the above optimization problem consists of two parts. The first part is the total achievable transmission rate, while the second part is the monetary cost that is required to achieve this rate. We assume that a user pays a price that is proportional to the transmission power it invests. Moreover, the two parts of the objective function are taken into consideration with different weights (a and b respectively). The final constraint restricts each user to invest transmission power at a single time-frequency slot. To solve this problem we consider each time-frequency slot $s \in S$ separately and solve the following problem.

$$\begin{aligned} \underset{T_u(s)}{\text{maximize}} \quad & a\left(\frac{B}{N}\right)\log_2\left(1+\frac{T_u(s)G(u,s)}{I(s)}\right) - bc(s)T_u(s) \\ \\ \text{subject to} \quad & T_{min} \le T_u(s) \le T_{max} \\ & c(s)T_u(s) \le C^u_{max} \\ & \left(\frac{B}{N}\right)\log_2\left(1+\frac{T_u(s)G(u,s)}{I(s)}\right) \ge R^u_{tar} \end{aligned}$$

In other words, we compute the optimal value of the objective function for each time-frequency slot and subsequently we choose the slot whose optimal value is the largest. To decrease the computational complexity of the above procedure, we exclude the time-frequency slots that satisfy one of the following conditions.

$$c(s)T^l_u > C^u_{max} \tag{3.4a}$$

$$\left(\frac{B}{N}\right)\log_2\left(1+\frac{T^h_u G(u,s)}{I(s)}\right) < R^u_{tar} \tag{3.4b}$$

Where T_u^l is the maximum between T_{min} and the minimum amount of transmission power required to achieve the target transmission rate and T_u^h is the minimum between T_{max} and the maximum transmission power for which the monetary cost constraint is satisfied. Slots that satisfy the condition (3.4a) cannot satisfy the monetary cost constraint while slots that satisfy the condition (3.4b) cannot satisfy the target transmission rate constraint, and thus, they cannot be chosen.

3.1.3 Price adaptation algorithm

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 providers will offer in a given market [22, 24, 36, 37]. Unlike them, this work does not assume that the demand is known. Moreover, it employs a price adaptation algorithm which assumes 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.

We consider an access market in which a set $P = \{p_1, p_2, ..., p_K\}$ of providers compete to offer services to end users. For each possible set of prices $\mathbf{x} = (x_1, x_2, ..., x_K)$ that is offered, each provider $p \in P$ achieves the revenue $F_p(\mathbf{x})$. The function $F_p : R^{K+} \to R$ is generally unknown due to the limited information that is available to each provider. Furthermore, in some scenarios, this function may be time-varying due to various dynamical phenomena such as (a) arrivals/departures of users, (b) user mobility, (c) changes in the channel conditions.

Our price adaptation algorithm approximates the function F_p with a concave polynomial of second degree $g_p(\mathbf{x}) = \mathbf{x}^T \mathbf{A_p} \mathbf{x} + \mathbf{k_p}^T \mathbf{x} + v_p$ and estimates its parameters based on the history of the game evolution. Specifically, each provider maintains a dataset

$$D_p = \{\mathbf{x}(i), F_p(\mathbf{x}(i))\}_{i=n-M_p,...,n-1,n} \tag{3.5}$$

where $\mathbf{x}(i)$ represents the ith set of prices that has been offered in the market and M_p corresponds to the number of previous price sets that are stored in the dataset D_p. To compute the parameters of the polynomial $g_p(\mathbf{x})$ each provider solves the following optimization problem.

$$\begin{aligned} \underset{\mathbf{A}_p,\mathbf{k}_p,v_p}{\text{minimize}} \quad & \sum_{i=n-M_p}^{n} w^{n-i}(g_p(\mathbf{x}(i)) - F_p(\mathbf{x}(i)))^2 \\ \text{subject to} \quad & g_p(\mathbf{x}) = \mathbf{x}^T\mathbf{A}_p\mathbf{x} + \mathbf{k}_p^T\mathbf{x} + v_p \\ & \mathbf{A}_p \preceq 0 \end{aligned} \tag{3.6}$$

Where w takes a value between 0 and 1 and defines the weight with which previous price sets are taken into consideration.

The above optimization problem is a semi-definite program and can be solved efficiently [44] . We constrain our polynomial to be concave for two reasons (a) to better capture the characteristics of concave payoff functions, and (b) to ensure the stability of the price adaptation process that is performed according to the following rule.

$$x_p(n+1) = x_p(n) + \mu \left.\frac{\partial g_p(\mathbf{x})}{\partial x_p}\right|_{\mathbf{x}=\mathbf{x}(n)} \tag{3.7}$$

where μ is the step size.

To initialize our algorithm, we take into consideration that the price 0 corresponds to revenue 0 for all providers. Moreover, each provider starts by offering a very small price (0.01 in our simulations). The initial estimation of the polynomial parameters is based on these first observations. Due to the limited number of available points in the dataset D_p, at the beginning of the experiment, the solution of the problem (3.6) may require a large number of Newton steps. In this case, we restrict the number of steps to be lower than a threshold. This leads a crude initial estimation of the polynomial that is improved as the size of the dataset increases.

Alternatively, we could initialize our algorithm by solving a least-norm problem (minimize the Euclidean norm of the vector that contains the polynomial parameters) instead of a least-squares problem until the size of the dataset D_p becomes larger than the number of the polynomial parameters.

Finally, at the beginning of the experiment, the polynomial parameters are re-estimated every time a provider $p \in P$ adds a new point to the dataset D_p.

When the size of the dataset becomes larger than a threshold, the parameters of the polynomial are renewed once for every L (in our simulations 10) new points that are added to the dataset D_p. This decreases the computational complexity of the algorithm. The price adaptation is still based on the rule (3.7) using the most recent estimation of the polynomial.

3.2 Simulation platform

The simulation platform can instantiate access markets with cellular providers, owners of spectral resources, that offer wireless access via their BSs to clients in a small city. The providers divide their channels to time-frequency slots according to a TDMA scheme. In these markets, two types of customer 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*.

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 ($a = 1$ and $b = 0$ in problem 3.2). 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 willingness to pay and target-transmission rate thresholds ($a = 0$ and $b = 1$ in problem 3.2). We may also define other types of customer profiles by appropriately choosing the weights a and b in the objective function of problem 3.2 .

Clients generate requests to connect to a BS (i.e., *calls*). The durations of calls and disconnection periods are given by appropriate stochastic processes. For example, in this work we considered two different types of client demand models, one with constant and one with varying demand. In constant demand, clients are always willing to remain connected, thus their demand can be viewed as a single call that lasts for the entire duration of the experiment. On the contrary, in varying demand, clients generate calls of limited duration and between two consecutive calls there is an interval in which a client remains disconnected.

In the current version of the simulation platform, clients move only when they are not performing calls and 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 traveled 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.

Finally, the simulation platform maintains the *umap*, 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. 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 work, 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. A description of the matlab functions that implement the simulation platform is provided in Appendix A.

3.3 Performance evaluation

To evaluate the proposed framework and simulation platform we instantiated two cellular markets with two providers that offer wireless access to users. In the first market users are stationary and are willing to remain connected for the entire duration of the experiment, which is relatively small (2000 seconds). On the contrary, in the second market, users are moving with pedestrian speed and are characterized by varying demand. These assumptions allow us to study the evolution of the market in longer periods (on the order of a month).

3.3.1 Market 1: stationary users with constant demand

3.3.1.1 Description

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. 3.1. 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. The parameters of the cellular networks of the two providers are summarized in Table 3.1. Note that a single time-frequency slot can be offered to only one user. Also, the demand of each user is exactly one slot.

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

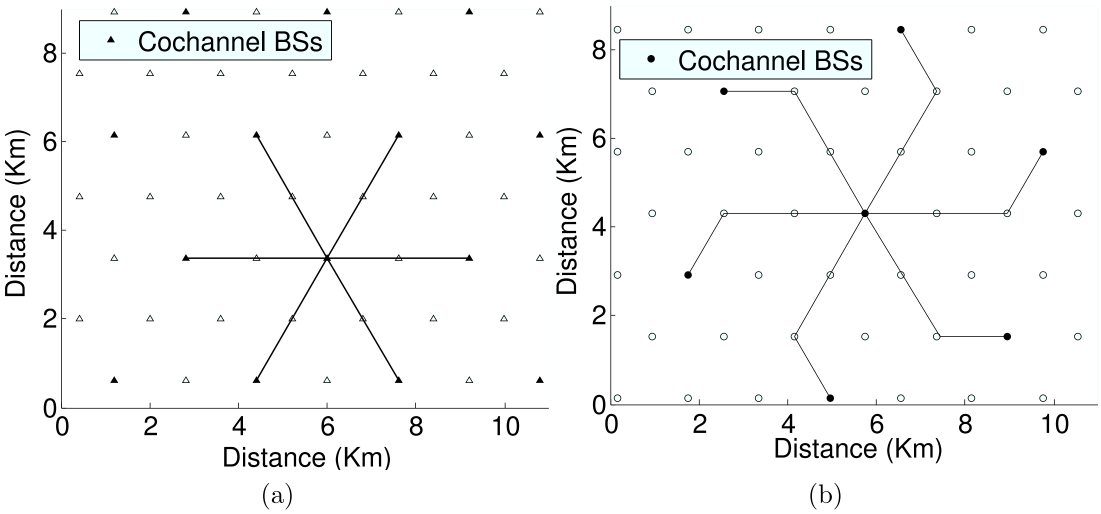


Figure 3.1: Closest BSs using the same frequency band when the spatial reuse factor is 4 (left plot) and 7 (right plot).

the Zipf topology (shown in Fig. 3.2), 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. 3.2). 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

Table 3.1: **Cellular network parameters**

Parameters	**Provider 1**	**Provider 2**
Bandwidth (MHz)	5.6	5.6
Channel width (MHz)	0.2	0.2
Slots per channel	3	3
Spatial reuse factor	4	7
Distance of two neighboring BS (Km)	1.6	1.6
Distance to the closest interfering BS (Km)	3.20	4.23
Slots per Base station	21	12

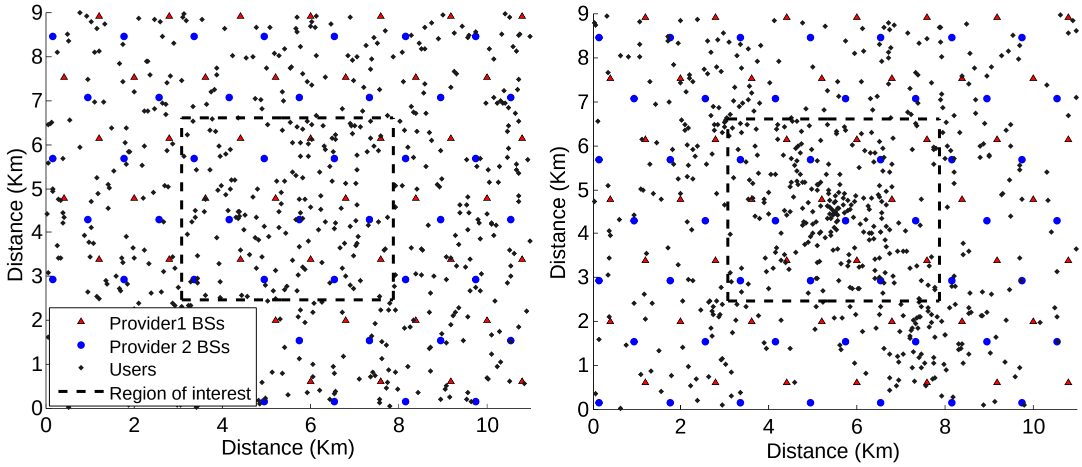


Figure 3.2: Uniform topology (left), Zipf topology (right).

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.

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 3.1.3. 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. 3.4, for a Uniform topology with rate preference) are average statistics over 30 Monte Carlo runs. This simulation testbed was implemented in Matlab.

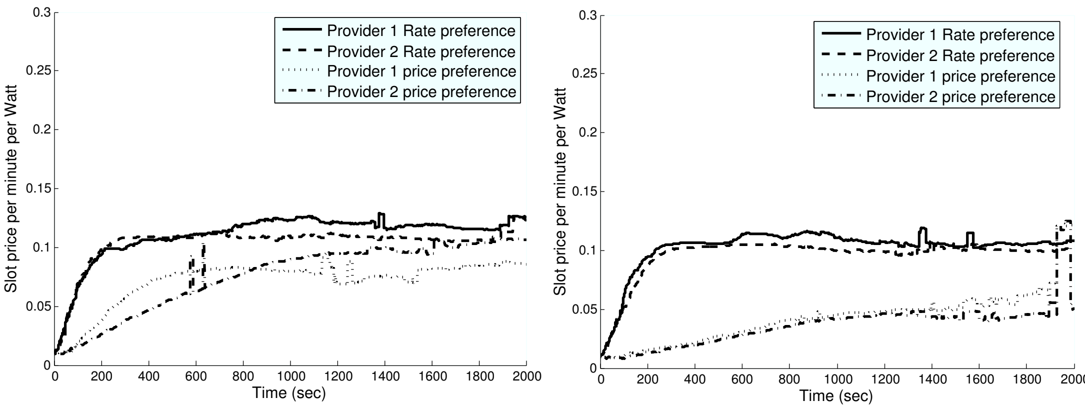
3.3.1.2 Simulation results

In rate-preference, a user connects to the BS that offers the best channel in terms of received signal to interference plus noise ratio (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. 3.3 presents the evolution of prices under the two topologies and user preference metrics, while Fig. 3.4 summarizes the 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,



(a) (b)

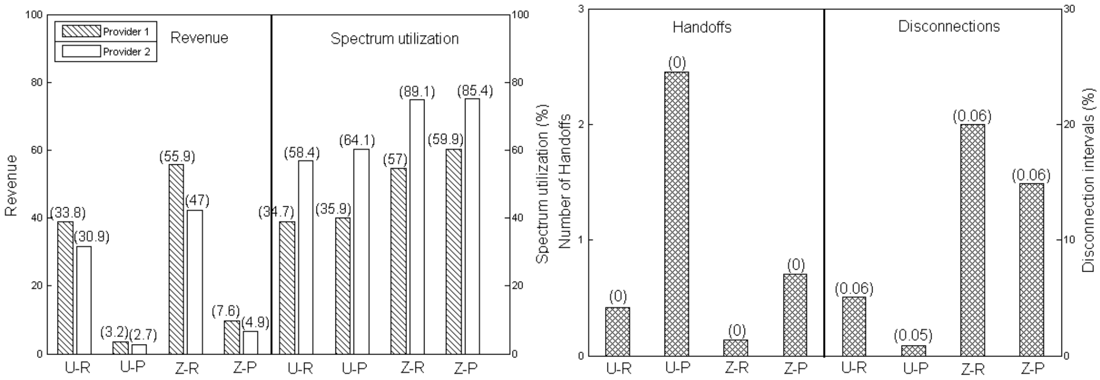
Figure 3.3: (a) The price evolution in the Zipf topology, (b) The price evolution in the Uniform topology.

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.3.4 (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



(a) (b)

Figure 3.4: (a) Provider revenue (left) and spectrum utilization (right), (b) User handoffs (left) and disconnection intervals (right).

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.

3.3.2 Market 2: moving users with varying demand

3.3.2.1 Description

In this market, we assume that the parameters of the cellular networks of providers are the ones described in Table 3.1. Moreover, 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. The two BS deployments are shown in Fig 3.5

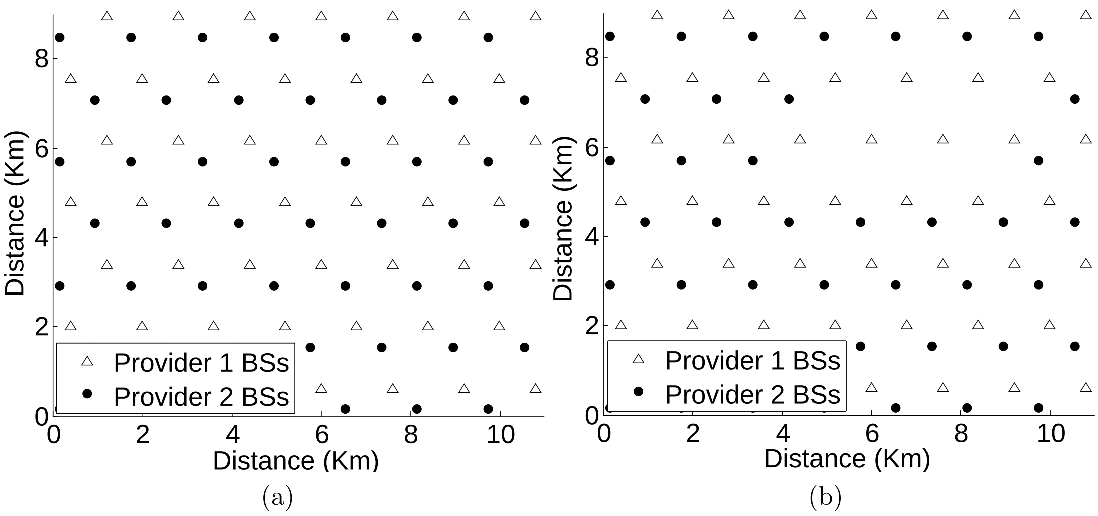


Figure 3.5: Uniform BS deployment (left), non-uniform BS deployment (right).

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* ($m = 0.15$, $\sigma = 0.0374$) and *high price tolerance* ($m = 0.2$, $\sigma = 0.0374$). We also simulated client populations with a *normal target transmission rate* ($m = 0.1$, $\sigma = 0.01$) and *high* *target transmission rate* ($m = 0.2$, $\sigma = 0.01$). A client generates a sequence of call requests. The call duration follows a Pareto distribution ($x_s = 3.89$, $a = 4.5$) of mean 5 min, while the disconnection period follows a Log-normal distribution ($m = 3.22$, $\sigma = 0.37$) of mean 27 min. 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 to the same BS for the entire duration of the call.

Providers use the polynomial-based approximation of their payoff function (as described in Section 3.1.3) to determine the prices for card clients dynamically, at time instances generated by a Poisson process with a mean rate of 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.

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 3.2). Each scenario simulates a *homogeneous* client population with respect to preferences and thresholds. Specifically, "P" scenarios correspond to a price-preference population, while "R" scenarios to a rate preference ones. For each scenario in Table 3.2, we simulated two client populations, one with price-preference (P) and another with rate-preference (R) (Fig. B.30). Note that in partial monopoly (rnd) scenarios, subscribers select randomly their provider while in partial monopoly, they choose provider based on the information that is available on the u-map (described in Section 3.2). Each run represents the evolution of the market in a microscopic level 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.

Table 3.2: **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

3.3.2.2 Simulation results

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. 3.7 (a)&(b)). 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. 3.6 (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). These results are similar to the ones reported in Section 3.3.1.2. In the case of increased target rate, as expected, the blocking probability also increases (Fig. 3.7 (a)). 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*

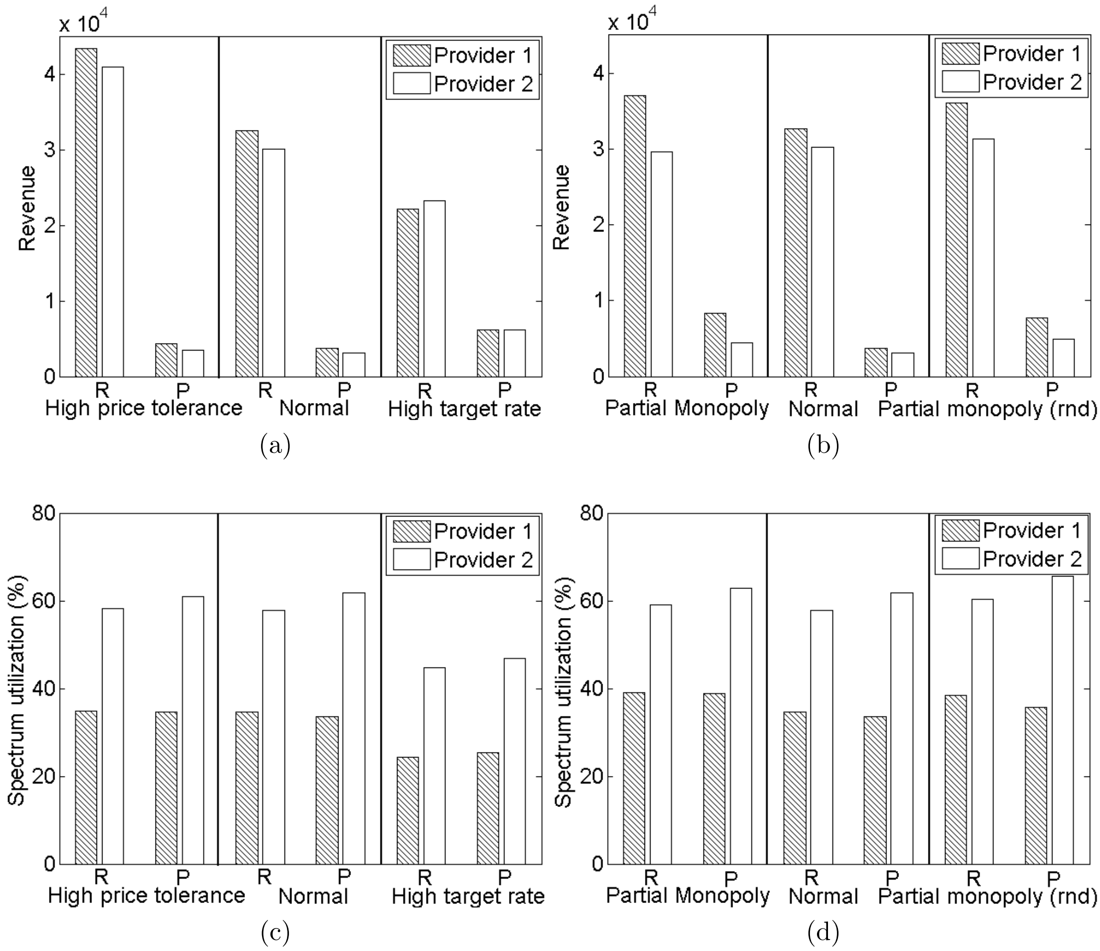
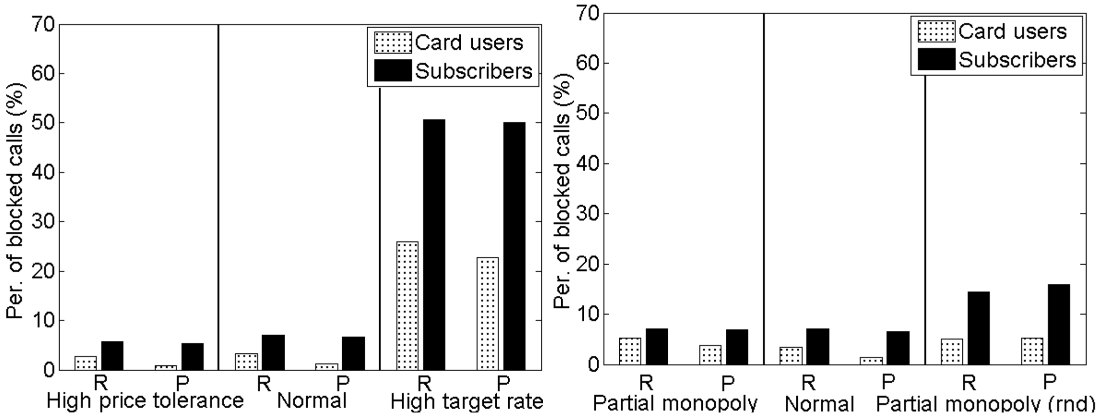


Figure 3.6: Main results for providers: Revenue (a) and (b). Spectrum utilization (d) and (e). Averages over 10 simulation experiments, each lasting 30500 min.

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



(a) (b)

Figure 3.7: Main results for clients: Percentage of blocked calls (a) and (b). Averages over 10 simulation experiments, each lasting 30500 min.

to satisfy the increased data rate requirement. This allows providers to increase their prices, and thus, their revenue. (Fig. 3.6 (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. 3.7 (a) and 3.6 (c)). Interestingly, these changes are small, due to the interdependency 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. 3.6 (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. 3.7 (b)). 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 willingness to pay 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.

Chapter 4

Flexi-card: a new service in cellular-based access markets

The expectation that the commercial deployment of CRNs will lead to improved network services has triggered numerous research and industrial activities and discussions about the dynamic spectrum access and sharing mechanisms. Traditionally, cellular wireless networks are managed by operators, which offer a fixed part of the spectrum to their customers via subscription mechanisms. Subscribers and pre-paid card users are associated with a certain operator to access the spectrum. However, new paradigms in both the wholesale and retail spectrum market and service models are being formed. Unlike the traditional cellular-based markets, these spectrum markets have larger sizes (in terms of number of potential providers), are more heterogeneous (in terms of services, clients, and providers), and potentially can offer an improved set of services (e.g., higher multiplexing gains and a reduction of costs due to the higher utilization of existing infrastructure).

As the wireless access and use increases, customers are differentiated even more by their usage and data-rate requirement profile. Often subscribers with relatively high usage pattern are subsidized by the ones with lower usage demand. As the cognitive radio technology advances, an even more diverse set of services will be available. To this end, we proposed the novel paradigm of a card client that is not associated with a specific operator and can dynamically access BSs of different infrastructures and operators based on various criteria, such as its profile, the network conditions, and the offered prices. Specifically, card users are flexible to select the appropriate operator on a per-call basis. This “flexi-card” paradigm, which has been assumed as a typical access paradigm in wireless LANs, could be a new type of service offered in cellular-based access markets. A similar concept is the “soft” (or virtual) SIM cards.

This work models a cellular market, its providers and a population of clients, highlighting the impact on the new service paradigms of card users on the evolution of the market and the welfare. Customers could dynamically decide to buy a *long-term subscription* or become *card* users. As card users, they can decide about their provider on a per-call basis, while as subscribers they are associated with a specific provider for the entire duration of their contract. The decision making process of a client for selecting the appropriate service paradigm takes into consideration the constraints, demand, and QoE criteria of that client.

We also consider different customer populations and analyze the flexi-card service from the perspective of regulators, users, and operators, possibly with conflicting objectives. A primary role of regulators is to promote competition and social welfare, a fair inclusive treatment of various user populations with respect to 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. On the other hand, the revenue maximization is the primary objective of providers.

The introduction of the card service rises several research questions: Will this additional service paradigm improve the social welfare by providing more options to customers? What is the impact on the benefit of customers, revenue of providers and market share? Are more or less users excluded from the wireless access due to the market prices offered? Would card service be a viable option for operators and a way to differentiate their services and attain more revenue? How does the traffic demand and customer profile shape the decision making mechanism and market share of customers? Would subscriptions “die out” and card users dominate the customer population? How does the market “treat” the different customer populations? What are the related pricing decisions of the operators and how they affect the outcome?

Our modeling framework allows us to perform an in-depth performance analysis of a cellular duopoly market where providers compete for a *diverse* population of customers who can access *two different services*. This is an important contribution of this work since most related approaches focus on just one good. It is important to note that claims on optimality made on various related approaches (e.g. [48, 49, 50]), with respect to the revenue of providers, the social welfare, and market efficiency, though valid in their context where providers compete for selling one good for a certain price, may not hold in our setting. In general, product differentiation allows for a finer market segmentation and can further increase the revenue of providers. In our model, there are two goods to be offered to the market, and thus, two different prices to be offered for those goods: the pricing decisions of the network operators are more complicated but at the same time allow for a finer partitioning of the market and possibly higher participation for users and revenue for the operators. That is, users that may have been "excluded" in a market where only long-term contracts are offered, due to the fact that their communication needs and respective willingness to pay do not justify entering this market, could now consider beneficial the good of "cards", thus increasing the overall market pie. This market exhibits several complexities due to the interplay of several parameters (e.g., the dynamic decisions of clients, their multiple options, the competition among providers, the diverse customer profiles) both in time and space.

4.1 Modeling framework and simulation platform

The modeling framework is fully configurable and parameterized based on the channel, infrastructure and network topology, type of users (e.g., service, demand, mobility, constraints, preferences, decision making processes), providers (e.g., price estimation, services), and available information. We have developed a detailed simulation environment of this framework, which is modular, in that, it can instantiate and implement different models for these parameters.

4.1.1 Cellular topologies

Each provider has deployed a cellular topology that offers wireless access via its BSs to clients in a small city. The providers divide their channels into time-frequency slots according to a TDMA scheme. To simulate the channel quality, we employed the *Okumura Hata* path-loss model for small cities considering the contribution of shadowing to the channel gain [46, 47]. The interference power at a BS during a time frequency slot is computed considering the contribution of all interfering devices at cochannel BSs.

4.1.2 Clients

When entering the market, a client needs to select an appropriate service or remain disconnected. Two customer types are considered, namely, the subscribers and card users, with their corresponding service types of subscription and flexi-card, respectively. A card user may select a BS of *any* provider, while a *subscriber* of a certain provider connects *only* to BSs of *that provider*. Service selections of clients are performed in a synchronized manner and change periodically. The time interval between two consecutive service selections of clients is denoted as epoch, and is of fixed duration. During an epoch, clients generate requests to connect to a BS to start a *call* (i.e., flow). The duration of calls and *off durations* (i.e., time interval between the end of a call and the start of the immediately next one of the same customer) are given by appropriate distributions. Specifically, the *call duration* follows a Pareto distribution, while the *off duration* is generated according to a Lognormal distribution (as were modeled in our empirical-based modeling work [51]). At the beginning of each call, a client selects a BS and remains connected to this BS for the entire duration of the call.

The utility of a client when selecting a service or a BS to perform a call, depends on its profile, which includes the *constraints, demand*, and *preferences* of that client. The constraints of a user are quantified by four thresholds: two thresholds for the service selection and two thresholds for the BS selection. The constraints of a user u for the service selection are expressed by its *willingness to pay for a service* (e.g., $T(u)$) and its call *blocking probability* tolerance threshold ($B(u)$). Moreover, the constraints of a user u for the BS selection are, its *will-*

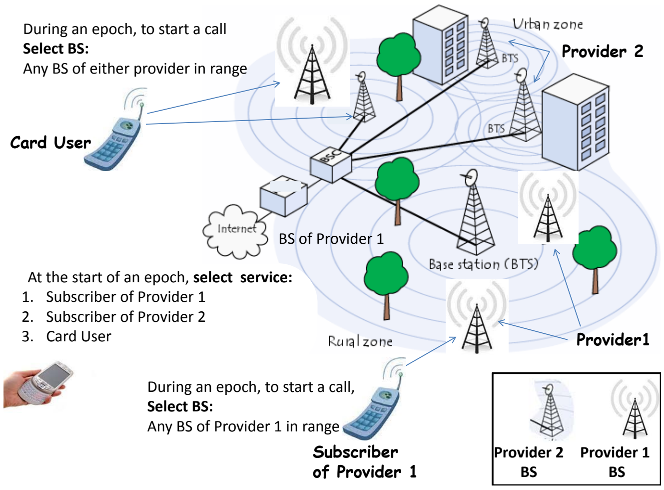


Figure 4.1: An example of a cellular-based duopoly with a card user and a subscriber.

ingness to pay for that call and the *minimum acceptable data-rate*. On the other hand, the preferences indicate the selection criterion, which can be either based on the monetary cost of the service or the QoE (e.g., the data-rate, call blocking probability). The preference criteria are used for *selecting a service type* as well as *selecting a BS*. In service selection, a client takes a decision that optimizes the metric that reflects its preference with respect to the blocking probability or the cost. Specifically, in the case of a cost-conscious customer, the client selects the service that minimizes its cost spending, while a QoE-conscious customer selects the service that minimizes the blocking probability. In BS selection, a client connects to BS of its wireless range based either on the data-rate or price criterion. Specifically, a price-conscious client selects the BS that *minimizes its cost spending*, while QoE-conscious clients select the BS that *maximizes their achievable data-rate*. For the service selection, a client expresses its preference with respect to cost and blocking probability, while for the BS selection, the preference is over cost and data-rate. For example, a client may select its service type based on the blocking probability criterion and the BS based on the price criterion. 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.

4.1.3 u-map

The market assumes the presence of a user-centric data repository that maintains information about the customer population. The u-map is a data structure that corresponds to a grid-based representation of a region. At the end of an epoch, each client reports the percentage of blocked calls and its service type at the u-map. The call duration, status, customer id, and provider id are recorded at the u-map. Statistics on the mean, median, and maximum blocking probabilities across all subscribers of the same provider are computed and reported at the u-map, taking into consideration the values reported by clients at the end of an epoch. Providers report their subscription and card-rates at the u-map. Furthermore, each client reports information about its constraints, demand, and preferences at the u-map.

4.1.4 Decision-making process of clients

The decision-making process of a client involves *long-term* decisions made at the beginning of each epoch for selecting the service type for that epoch and *short-term* decisions for selecting the appropriate BS at *a per call basis*. For each of the three service options, namely, to become subscriber of the Provider 1, subscriber of the Provider 2, or card-user, *the service constraints need to be satisfied*. Specifically, a client first checks whether the total cost for that service is under its willingness to pay threshold *as well as* the estimated blocking probability with that service is under the blocking probability threshold. A client needs to estimate the blocking probability for each of the above services. Specifically, the blocking probability of subscribers of a certain provider is estimated as the average blocking probability as reported by all subscribers of that provider during a number of previous epochs, at the u-map. Similarly, the blocking probability for the card service is estimated as the average blocking probability of all card users during the same period of multiple epochs, as reported at the u-map. After the service-type selection, during an epoch, clients make calls and, for each call, a client can select a BS in its wireless range that satisfies its willingness to pay and data-rate thresholds. The data-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 [52].

A client becomes *disconnected* when *any* of its constraints for the *service* selection can *not* be satisfied. Otherwise, the user chooses a service type (subscriber with one of the two providers or card user) according to its preference with respect to blocking probability and price. A call can be *successful* or *blocked*. An unsuccessful selection or association process with a BS results to a blocked call. Specifically, a call is blocked when *any* of the client constraints for the *BS selection* can *not* be satisfied by any BS in the wireless range of the client or *all* the channels of these BSs have been serving other calls.

4.1.5 Providers

Providers perform two decision making processes, namely, (a) the estimation of their subscription rate at the start of each epoch, and (b) the estimation of the card rate that takes place multiple times during an epoch. The subscription rate is decided at the start of an epoch and remains fixed during that epoch, while the card rate is updated multiple times during the epoch. The subscription charging scheme is a two-parameter tariff that includes a *flat-rate* (e.g., p) for an *up to a certain total call duration* (e.g., D_{flat}) and a *fixed per-minute per watt of transmission power cost* p_0 that charges for any extra call duration. The flat-rate price p is determined at the subscription rate estimation process. For example, a subscriber u with demand $D(u)$ that buys a subscription with a rate p, will pay p if $D(u) \leq D_{flat}$, whereas, if its total call duration exceeds D_{flat}, it will be charged of $p_0 * \tau * d$, for each extra call of duration d, during which, it invests transmission power of τ. The card charging scheme is a simple *linear* tariff which charges the calls per minute and Watt of transmission power. These pricing schemes that charge the clients proportionally to the transmission power they invest aim to penalize an aggressive increase of the transmission power.

4.1.6 Subscription rate estimation

In subscription rate estimation, the objective of a provider is to maximize its revenue. We assume that each provider knows the distribution of the demand, constraints and preferences of all clients, as provided by the u-map. The approach is myopically greedy, in the sense that it determines the price that maximize its revenue for the upcoming epoch, assuming a fixed price of its competitors, an average card rate (based on the card rates announced during the previous epochs by all providers) $\hat{p}_c$, and knowledge of the demand, preferences, and constraints of all clients (via the u-map). At the beginning of each epoch, a provider determines the subscription rate and announces it to the market, then each client can make its service selection.

To estimate its revenue, each provider *emulates the market offline* and the decision making process of all clients (based on their profile recorded at the u-map). Specifically, the provider knows the demand distribution of each client, its constraints, and emulates the service selection process of this client. As mentioned earlier, the constraints of a client (namely, its blocking probability and willingness to pay) need to be satisfied. To perform this estimation, the provider should be able to predict the blocking probability of all available services (subscription and card services) for all possible sets of subscription rates that could offered in the market. We assume, that providers predict the blocking probability using the following sigmoid-based model:

$$B(p_1, p_2) = \frac{1}{1 + e^{a_1 p_1 + a_2 p_2 + b}} \tag{4.1}$$

Where p_1, p_2 are the subscription rates offered by the provider 1 and 2 respectively. Each provider employs a sigmoid model, not only to predict the blocking probability of its own subscribers, but also the blocking probability of the subscribers of its rival provider and the one of card users. This information is required for a provider to emulate the user decision making. The parameters of the sigmoid model, for all available services, are estimated by all providers simultaneously and are updated in a periodic manner (once every 20 epochs). The estimation of the model parameters is performed using least-squares fitting on data that are collected during the last 20 epochs. These data are average statistics that are computed based on information that is uploaded by all users on the umap.

After the emulation of the service selection of a client, a provider estimates the expected charge for this client based on its demand. Specifically, to compute the extra charge (over the flat rate fee) for the subscription service, the provider considers the average price per minute, that its subscribers paid when they exceeded their free time, during the last epochs. Similarly, the average charge per minute of card users is computed. Based on the offered subscription rates, the average card rates, and the user demand, the provider can estimate its revenue. After exploring the space of the possible prices, the algorithm reports as the subscription rate of the provider, the price p^* that maximizes its revenue, (given the announced subscription rate for its competitor).

4.1.7 Card rate estimation

The price estimation for card rates runs multiple times during an epoch, motivating the design of a more efficient algorithm. It is a novel algorithm based on the concept of *representative users*: Instead of considering the detailed characteristics of each individual customer/entity in our population, something impractical and unrealistic, we model the customer population using a *relatively small number of representative users*.

To determine the characteristics of "representative users", we consider that the city consists of a number of regions $R_k, k = 1, ..., K$. We also divide the duration of the experiment T into a number of non-overlapping intervals $T_m, m = 1, ..., M$. Finally, we denote the set of all calls that are performed during the experiment as H. A specific call $h \in H$ can be written as a triplet (h_u, h_a, h_τ) where h_u are the characteristics of the user that performed the call (willingness to pay and data-rate threshold) and h_a, h_τ are the location and the time instance at which the call was initiated. The characteristics of the "representative users" of a specific region R_k at a given time interval T_m are determined based on the dataset of calls that were performed at the same region during the previous time interval $H(k, m-1) = \{h \in H | h_a \in R_k, h_\tau \in T_{m-1}\}$. Specifically, the characteristics of the "representative users" are determined by applying a clustering algorithm on the dataset $H(k, m-1)$ (e.g., the K-means in this case).

To estimate the revenue of a provider at a particular time instance, the price of its competitor is assumed to remain fixed. The positions of the "representative users" of each region are according to a uniform distribution on the area of the region. The "representative users" take their decisions at a random order. Subsequently, the decision making of the "representative users" is simulated and the revenue of each provider is computed. This process is repeated for all prices that could be offered by the providers. We also employ multiple random realizations of the "representative-user" positions and order of their decision process (corresponding to multiple Monte Carlo runs) to increase the accuracy of our results. The prices are adapted by applying the best response algorithm.

4.2 Performance evaluation

4.2.1 Simulation scenarios

The simulation platform considers a small city, represented by a rectangle of 3 Km x 2.3 Km. Each provider has a cellular network that consists of 4 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. 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. Each client is associated with one BS during a given call. The maximum allowable transmission power that a client can invest is 2 Watts. A snapshot of the network topology is shown in Fig. 4.2.

There are 2000 clients in total, distributed according to a uniform distribution in the simulated region of this small city. The constraints of clients namely the willingness to pay and the blocking probability threshold for the service selection as well as the data-rate and the willingness to pay threshold for the BS selection, follow Gaussian distributions (their parameters are shown in Table 4.1). The

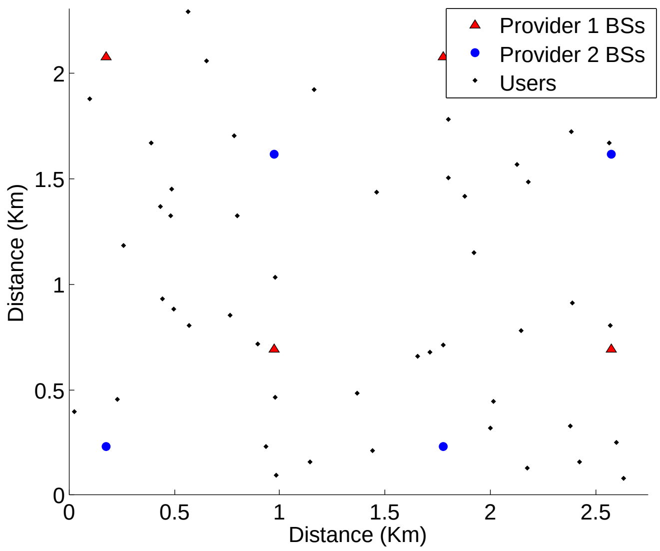


Figure 4.2: Network topology with users that are performing calls.

name convention "X-Y" indicates with "X" the service type selection criterion and with "Y" the BS selection criterion (as shown in Table 4.2).

Each client generates a sequence of call requests. The call duration follows a Pareto distribution ($x_s = 3.89$, $a = 4.5$) of mean 5 min, while the disconnection period follows a Log-normal distribution with different parameters for each user (μ is uniformly distributed in the interval [4.0679 6.2150] and σ is equal to 0.37) resulting in client demand varying from 33 to 267 minutes per epoch. 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

Table 4.1: **The thresholds of the client constraints follow Gaussian distributions**

Threshold	Mean	Standard deviation
Willingness to pay (service selection)	0.17	0.0374
Blocking probability	0.2	0.05
Willingness to pay (BS selection)	0.15	0.0374
Data-rate (Mbps)	0.1	0.01

Table 4.2: **Simulated scenarios**

Scenario	**Service criterion**	**BS criterion**
B-R	Blocking probability	Data-rate
B-P	Blocking probability	Price
P-R	Price	Data-rate
P-P	Price	Price

of the call.

We implemented the simulation platform and this market in Matlab. 10 Monte Carlo runs were performed for each scenario. The preferences and constraints of a client remain *unaltered throughout the simulation*. Each run represents the evolution of the market during a period of 160 epochs, each lasting 5 days (a 27-month period in total). This long duration is required in order to better observe the evolution of providers, their interaction with clients in this simulated small-city environment, and identify transient and steady-state phenomena. To highlight the impact of the flexi-card service, two market types were simulated: an *only-subscriber market* (baseline case), in which each customer has only the choice of becoming a subscriber with one of the providers or remain disconnected, and a *mixed market*, in which customers have the additional service option of becoming card users.

4.2.2 Analysis

This analysis evaluates the impact of service paradigms on the evolution of the market, using metrics that can provide insights to regulators, customers, and providers. The performance of a provider is characterized by its revenue, while the performance of a client is indicated by the blocking probability of its calls. Furthermore, we quantify the overall satisfaction of the society by computing the percentages of blocked calls, social welfare, market share, and percentage of disconnected users for the only-subscriber and mixed markets. The *percentage of blocked calls of a client* is the ratio of its successful calls over the total number of call requests. The social welfare is defined as the sum of the net benefit of all

Table 4.3: **Customer Populations**

Type	Willingness to pay	Blocking Probability	Demand
High-business	$>$ 80% percentile	$<$ 20% percentile	all range
Bargain-finders	$<$ 20% percentile	$>$ 80% percentile	all range
Low-profile	$<$ 50% percentile	all range	$<$ 20% percentile

users and providers. The net benefit of a provider is its revenue while the net benefit of a user is the difference of what the user was willing to pay and what the user actually paid for his/her calls. Our reported results are average statistics over all epochs and Monte Carlo runs.

We comparatively analyze the only-subscriber and mixed markets. We speculated that the presence of the card service will reduce the blocking probability (compared to the baseline case), and thus encouraging more clients to remain connected. Indeed, the presence of card service becomes a catalyst in the market! There is a dramatic decline of the number of disconnected users, a prominent reduction in the blocking probability in all scenarios, and an increase in the social welfare (as shown in Figs. 4.3a, 4.3b, and 4.3c, respectively). Note that due to the larger participation in the market, the social welfare attained is substantially improved, thus comprising further evidence of the merits of having the multiple service offerings in the market. We also observe that card users exhibit significantly lower blocking probabilities than subscribers in all scenarios.

We distinguished three customer populations, namely the *high-business, bargain-finder*, and *low-profile customers* (Table 4.3) and observed their performance in the context of the two markets. From the perspective of regulators, an important implication to the social welfare is the exclusion effect. To highlight how an only-subscriber market excludes certain customer populations (e.g., the ones of low demand and willingness to pay), we computed the percentage of such users that remain disconnected, and found that in the B-R scenario this percentage drops from 83% in the only-subscriber market to 65% in the mixed market. On the contrary , in the P-R scenario we observe a slight increase of the percentage of disconnected low profile users, from 78% in the only-subscriber market to 81% in the mixed market (Fig. 4.3d). This is due to the higher subscription rates in the mixed market (Fig. 4.4c).

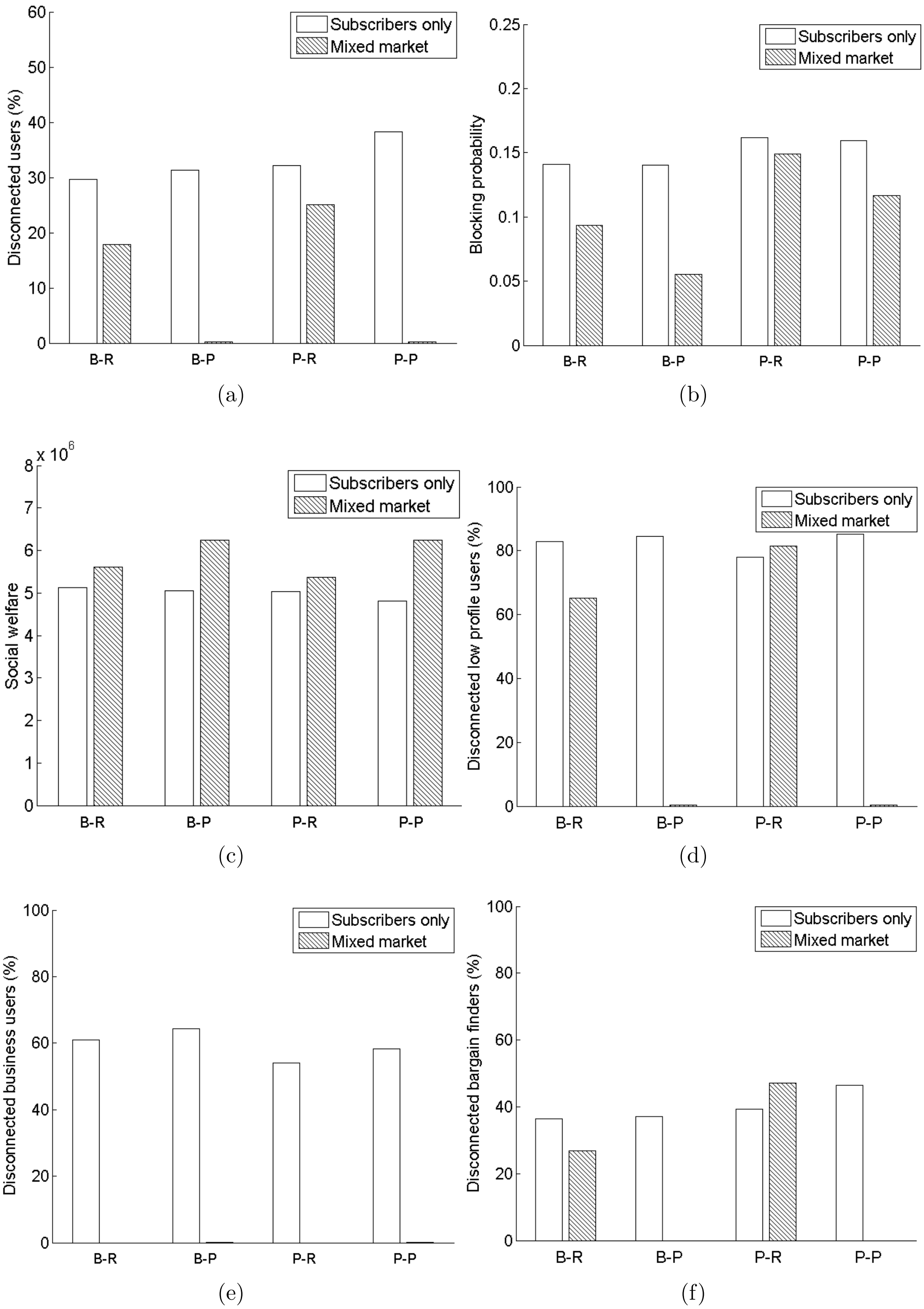


Figure 4.3: (a) Percentage of disconnected users. (b) Blocking probability. (c) Social welfare. (d), (e), and (f) Percentage of disconnected low-profile, high-business, and bargain-finder users, respectively.

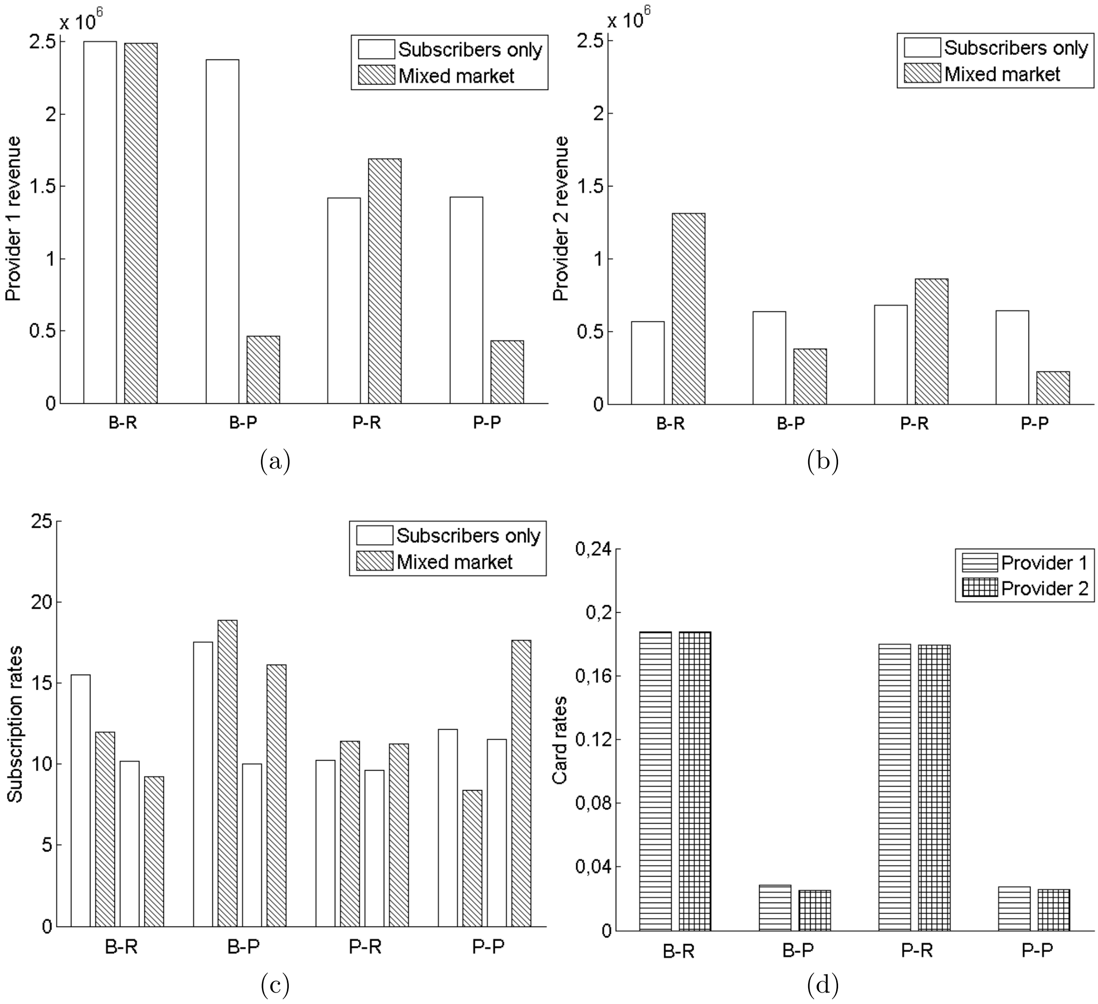


Figure 4.4: (a) The revenue of Provider 1. (b) The revenue of Provider 2. (c) The subscription rates. For each scenario, the left column corresponds to the Provider 1 and the right column to the Provider 2 of that market, respectively. (d) Card rates in the mixed market.

In the B-P and P-P scenarios the percentage of disconnected low profile users drops from about 83% in the only-subscriber market to 0% in the mixed market (Fig. 4.3d). Moreover, the percentage of the high-business disconnected users is close to 0 in all scenarios! (Fig. 4.3e). More statistics about the percentage of disconnected users of other customer profiles are shown in Figs. 4.3d, 4.3e, and 4.3f. We will now focus on the specific scenarios:

4.2.2.1 Blocking probability criterion

The first part of this analysis focuses on the blocking probability as the criterion for selecting the service. For the BS selection, clients select the BS based on the data-rate or price criterion. The only-subscriber market shows very high percentages of disconnected users (e.g., up to 30%, as shown in Fig. 4.3a) and relatively high blocking probabilities (e.g., up to 0.14, as shown in Fig. 4.3b). In general, due to the higher channel availability of the first provider compared to the second one, that directly affects the observed blocking probabilities, the revenue of the first provider is larger. This difference is prominent especially in the B-R scenario (Fig. 4.4a, 4.4b). Interestingly though, a different charging behavior of the providers depending on the BS selection criteria (rate preference vs. price preference) can be observed: in rate preference, card users invest higher transmission power which will affect their total monetary spending, and of course, the revenue of the provider. On the other hand, in the B-P scenario, the price preference in the BS selection, forces the providers to keep their card rates relatively low, and thus, their revenue is lower than in B-R.

What is also interesting, and not necessarily expected, is that in the mixed market with rate preference (B-R as shown in Figs. 4.4a and 4.4b), not only the percentage of disconnected users and the blocking probability are lower but also the revenue of the second provider has increased substantially while the revenue of the first provider is almost unaffected. This means that the prices allow low- and high-consumption users to self select the most suitable product that matches their type, thus increasing participation in the market. Customers as subscribers tend to select the first provider that has the lower blocking probability (due to its larger channel availability). Although the subscription rate of the second provider is significantly smaller compared to the first provider (Fig. 4.4c), the blocking probability criterion for the service selection gives a distinct advantage to the first provider.

The card becomes the preferable service for customers sensitive to the blocking probability and data-rate and with higher willingness to pay threshold, which results to relatively higher card rates. The high-business customers in the mixed market always prefer the card service option, given that it offers them the lowest

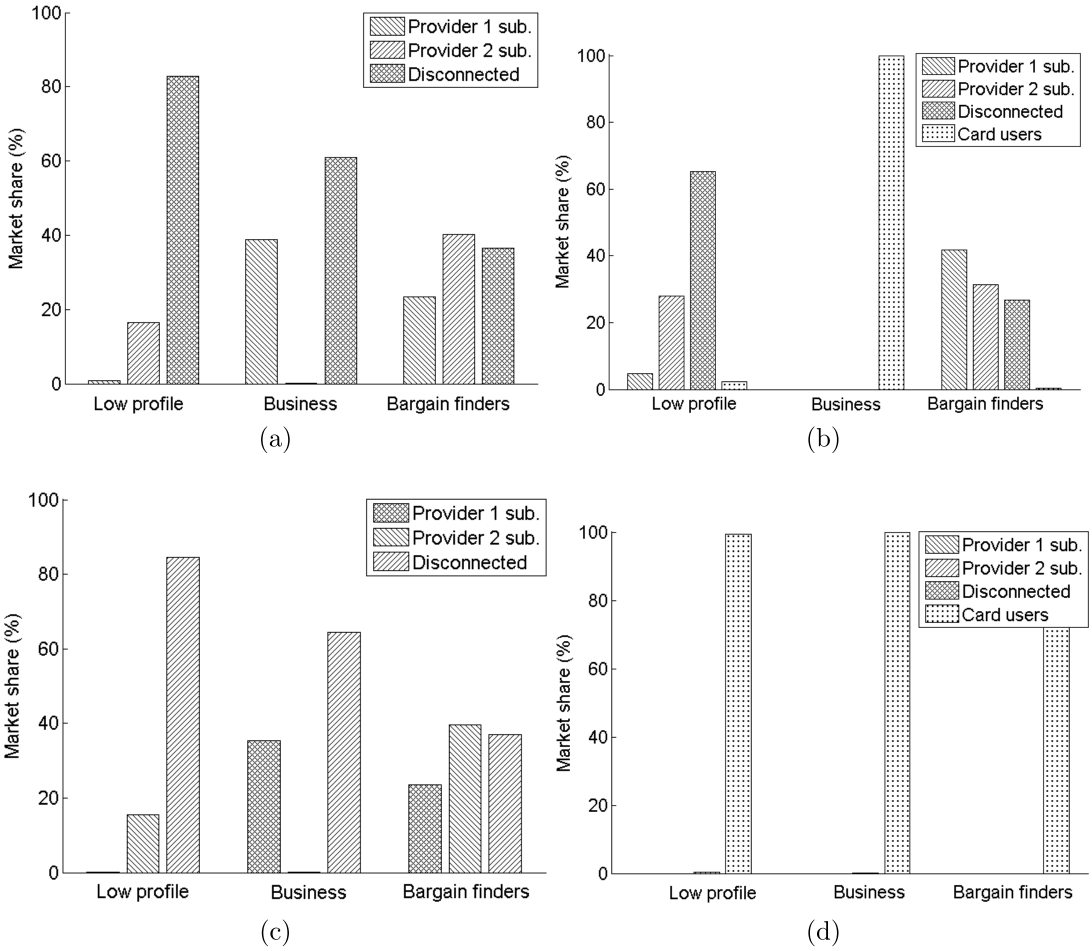


Figure 4.5: Market share in B-R: only-subscriber market (a), mixed market (b). Market share in B-P: only-subscriber market (c), mixed market (d)

blocking probability (Fig. 4.5b). As mentioned earlier, unlike the only-subscriber market, in the mixed market, there are no disconnected high-business customers.

In the B-R scenario, in both the only-subscriber and mixed market, the second provider attracts more bargain-finder and low-profile users than the first one (Fig. 4.5a and 4.5b) due to its lower subscription rate. Specifically, even if the blocking probability of the first provider is lower compared to the second one, its subscription rate is higher and cannot satisfy the willingness to pay threshold of the majority of the low-profile and bargain-finder users. These users have no other choice but to become subscribers of the second provider. In addition, the percentage of card-users from these populations is significantly lower than in

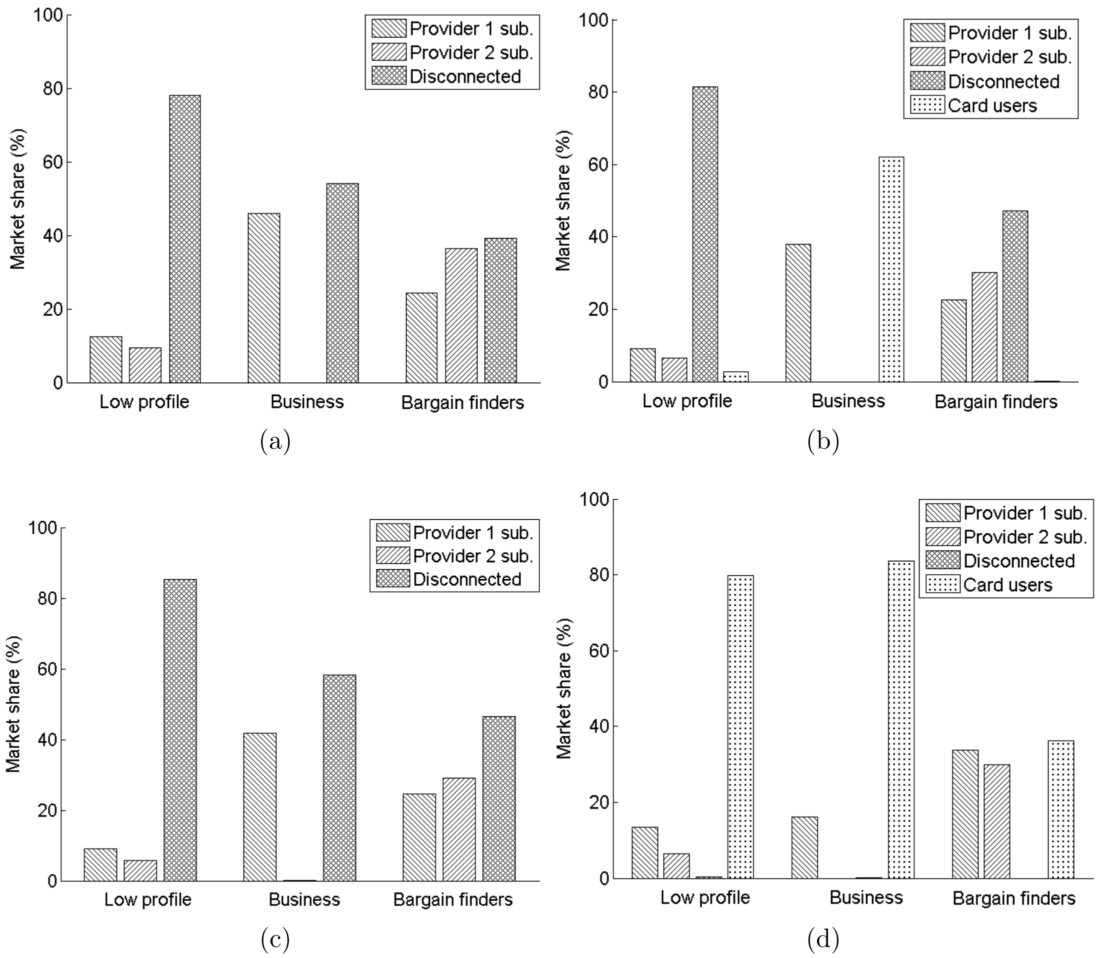


Figure 4.6: Market share in P-R: only-subscriber market (a), mixed market (b). Market share in P-P: only-subscriber market (c), mixed market (d)

the case of high-business customers, given the relatively higher rates of the card service. When the BS selection uses the price preference (i.e., B-P), the difference in the percentage of disconnected users in the mixed market compared to the only-subscriber is even more dramatic (31% vs. 0.18%, as shown in Fig. 4.3a). Similar reductions are observed in the per user and per call blocking probabilities (e.g., 0.14 compared to 0.05, as shown in Fig. 4.3b). Moreover, the price criterion intensifies the competition, which has as a result, a more prominent reduction in the offered prices, causing a steep decrease in the revenue of the first provider (Fig. 4.4a). Even more interestingly, the population of subscribers dies out!

Note that the price preference at the BS selection affects dramatically *the card rates*: the competition between providers results in a card rate reduction which encourages all customers to become card users (Fig. 4.5d).

4.2.2.2 Price criterion

The second part of this analysis focuses on the price as the criterion for selecting the service. For the BS selection, clients select the BS based on their preference, i.e., data-rate and price (P-R and P-P, respectively). The mixed markets still exhibit a very low percentage of disconnected users. At the same time, the price criterion in the service selection alleviates the advantage of the low blocking probability of the first provider resulting in a prominent reduction of its revenue (Fig. 4.4a and 4.4b). In addition, the competition of the providers in the offered subscription and card rates encourages more customers to become subscribers compared to the markets in which the blocking probability was the service selection criterion. The preference of users for lower prices over the blocking probability further increases the blocking probability.

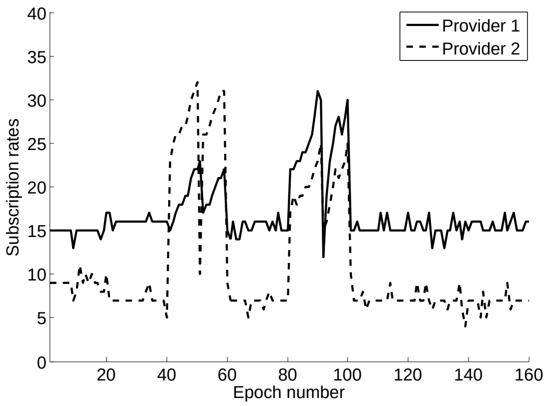
4.2.2.3 Additional discussion on price dynamics

A general trend in the mixed markets is that the difference of the card rates of the two providers is very small (as shown in Fig. 4.4d). This can be explained by the symmetry in the deployments of the two providers and the uniform distribution of clients in the region. As mentioned earlier, the card rates are determined and are affected by the BS selection mechanism, in which the position of the clients and the BS deployments play an important role. The card product market is actually a commodity market with an almost identical "market price" across all competing providers (same with price for any kind of commodity goods ranging from crude oil to Internet transit prices) [53]. In the cases of blocking probability and rate preferences, the card rates are relatively increased, compared to the subscription rates. On the other hand, in the case of price preference, the price criterion forces the providers to keep their offered card rates at relatively lower levels.

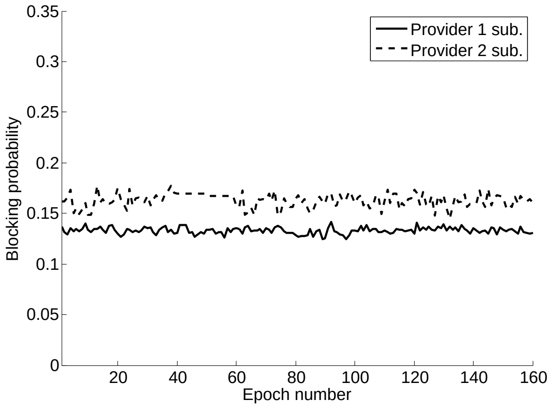
Notice that the only-subscriber market, the average subscription rate that is offered by the second provider is lower compared to the first provider (as shown in Fig. 4.4c). Moreover, the differences between the two subscription rates is larger in the B-R and B-P scenarios compared to the P-R and P-P scenarios. This is due to the advantage of the first provider in the blocking probability which significantly affects the client decisions in B-R and B-P. On the contrary, in P-R and P-P, price is the parameter that mostly affects the client decisions resulting in small differences between the subscription rates of the two providers.

Another parameter that affects the performance of providers is the blocking probability forecasting. As mentioned in Section 4.1.6, the providers predict the blocking probability of all services (subscription and card services) using a sigmoid-based model. The parameters of this model are re-estimated once every 20 epochs by fitting the data that are collected during these epochs to the model. Then, at each epoch, a provider chooses the subscription rate it will offer to the market based on the most recently estimated blocking probability prediction model. This methodology sometimes makes a provider choose a strategy that is not beneficial in terms of revenue. Specifically, the sigmoid model could be such, that a provider may believe that if it increases its price it would significantly reduce the blocking probability of its subscribers or it may affect the blocking probabilities of the subscribers of rival providers or even the ones of card users. This does not happen in practice and results in the provider achieving very low revenue. In most cases in which this phenomenon takes place we observe that in following intervals the parameters of the sigmoid model are corrected and the behavior of the provider becomes again profitable. To correct this pathology, we could increase the memory of the system when we estimate the parameters of the sigmoid model. Specifically, instead of relying only in data that are collected during the last 20 epochs, we may also take into consideration data that are collected before these epochs, perhaps with a smaller weight. That way the system will remember that certain choices of strategy are not beneficial and as such they will not be adopted again in future epochs. We present next the time series of the offered subscription rates, blocking probability, revenue, and market share of both providers in all simulated scenarios and we discuss the observed phenomena. These results correspond to one Monte Carlo run from each scenario.

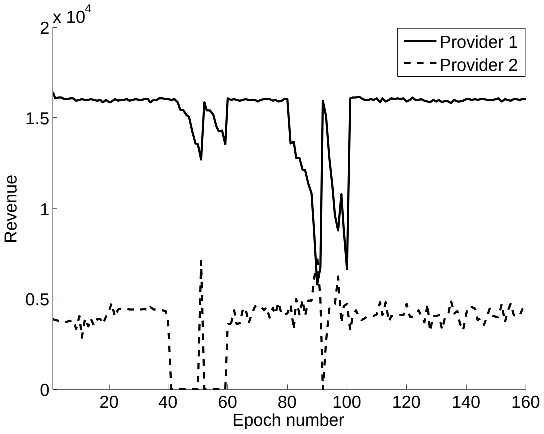
B-R: only-subscriber market



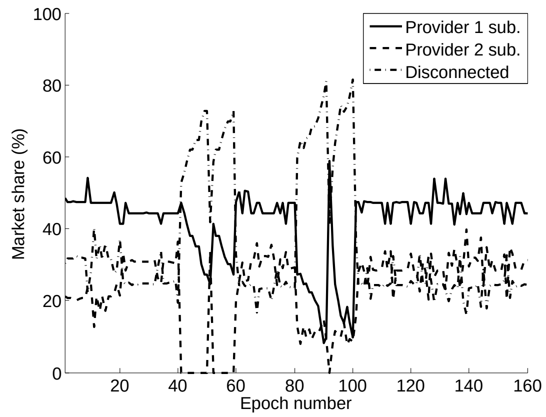
(a)



(b)



(c)



(d)

Figure 4.7: B-R only-subscriber market: subscription rates (a), blocking probability (b), revenue of providers (c), market share (d)

In the epochs 40 - 60 the sigmoid model is such, that the provider 2 believes, that if it increases its price it will reduce the blocking probability of its subscribers and at the same time increase the blocking probability of the subscribers of provider 1. The provider 1 also increases its price in the epochs 80 - 100 for similar reasons. Fig 4.7b indicates that the expectation of the providers are not met and the blocking probabilities are not significantly affected by their choices of strategy. Moreover, as indicated in Fig. 4.7c and 4.7d, in epochs 40 -60 and 80 - 100, the revenue and market share of both providers is decreased.

B-R: mixed market

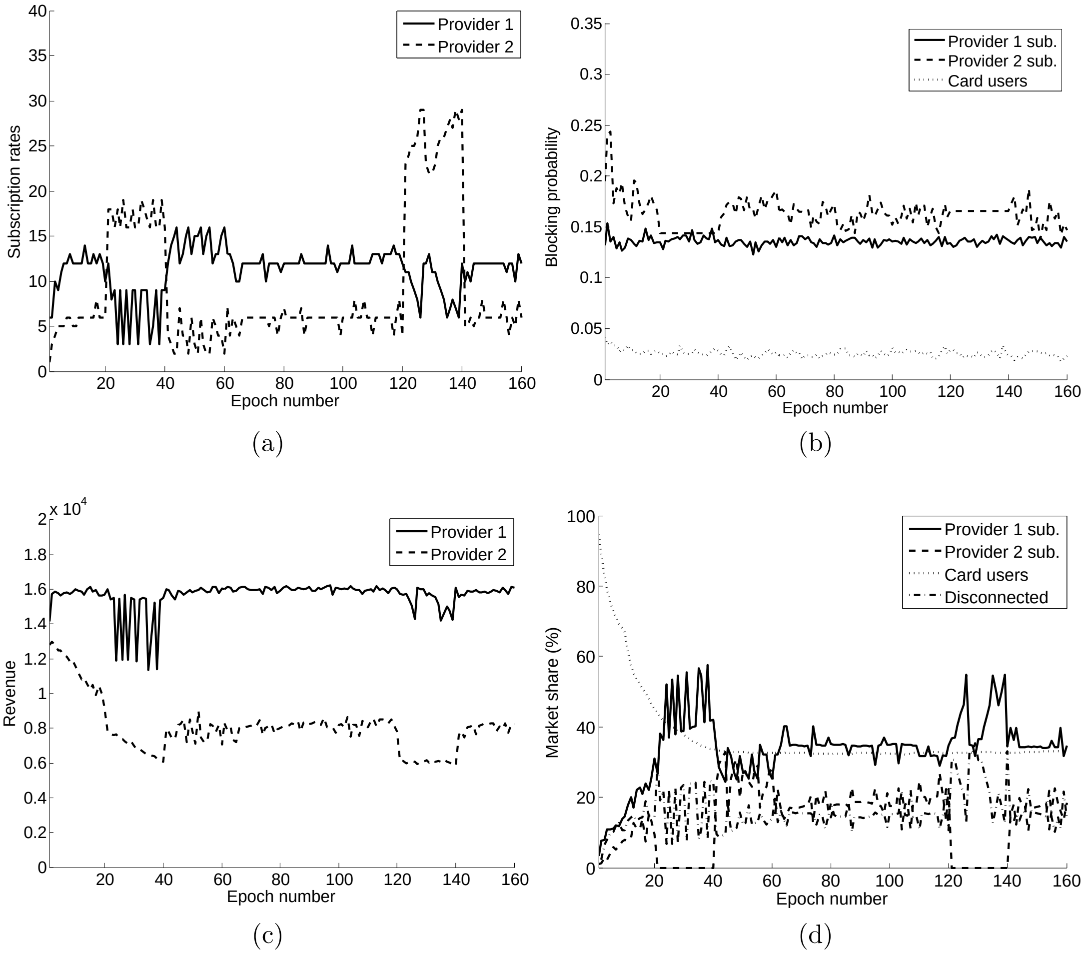


Figure 4.8: B-R mixed market: subscription rates (a), blocking probability (b), revenue of providers (c), market share (d)

In the epochs 20 - 40 and 120 -140, the parameters of the sigmoid model are such, that the provider 2 believes that if it increases its price it will decrease the blocking probability of its subscribers and at the same time increase the blocking probability of the subscribers of provider 1. On the contrary, the provider 1 believes that by decreasing its price, it will increase the blocking probability of the subscribers of the provider 2. In these intervals, providers pick a strategy which they believe that will result in their subscribers observing the lowest blocking probability, thus the provider 2 chooses a very high price and the provider 1 a very low price. Fig. 4.8b indicates that despite the predictions of the sigmoid model, the blocking probabilities are not significantly affected by the choices of the providers. This results in a decrease of their revenue as depicted in Fig. 4.8c.

B-P: only-subscriber market

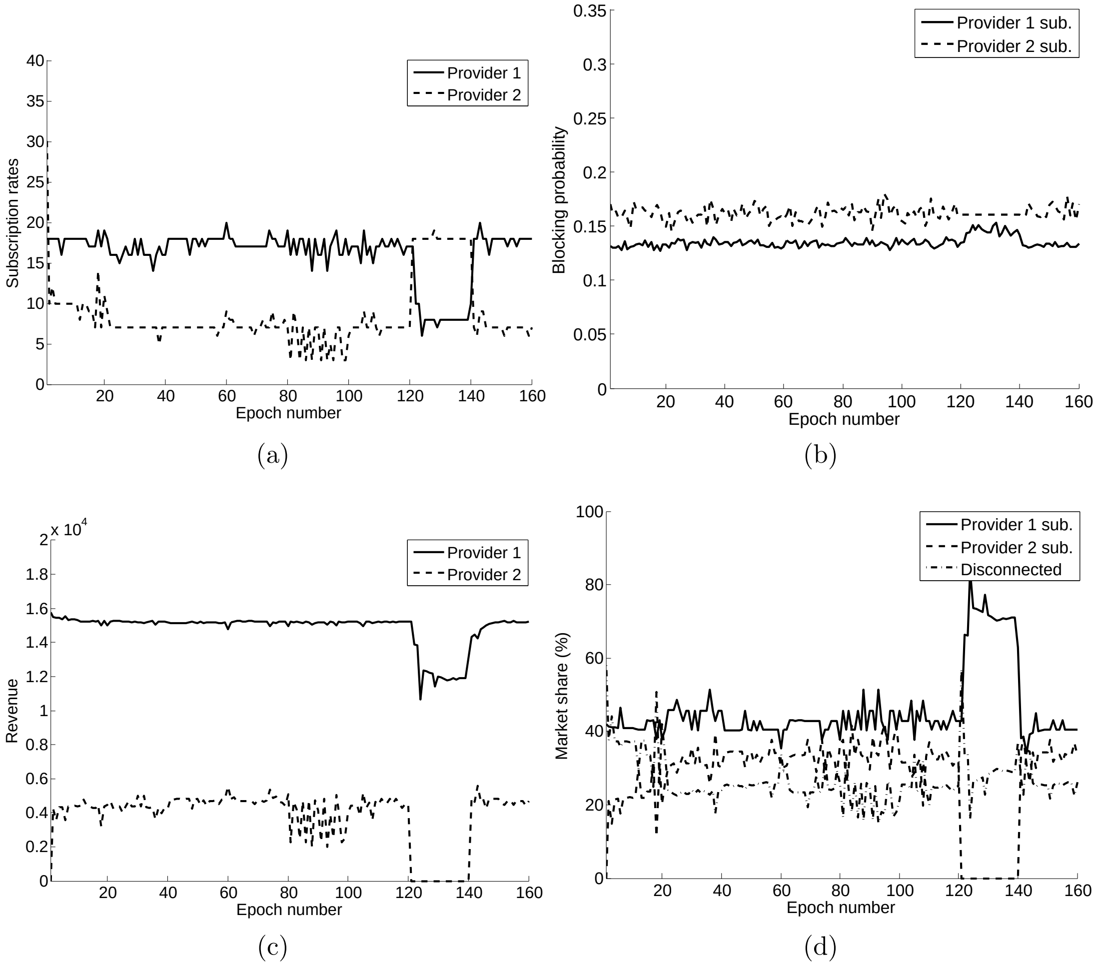


Figure 4.9: B-P only-subscriber market: subscription rates (a), blocking probability (b), revenue of providers (c), market share (d)

In the epochs 120 -140 , the provider 2 believes that its blocking probability is lower compared to provider 1 and increases its price to achieve more revenue. Similarly, the provider 1 assumes that its blocking probability is higher than provider 2 and thus it decreases its price to attract customers that cannot become subscribers of the provider 2 due to its increased subscription rate. However, Fig.

4.9b and 4.9c indicate that the predictions of providers are not met which results in a decrease of their revenue.

B-P: mixed market

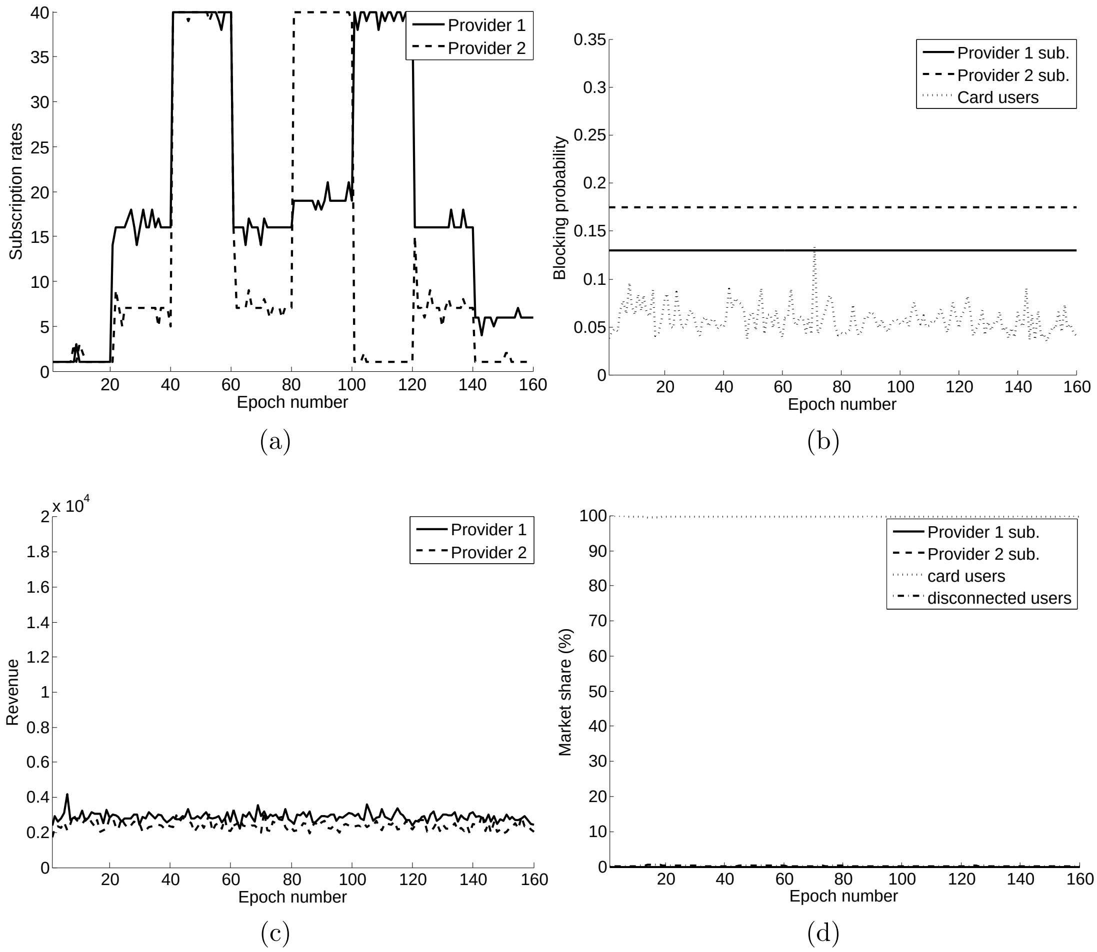


Figure 4.10: B-P mixed market: subscription rates (a), blocking probability (b), revenue of providers (c), market share (d)

Fig. 4.10d indicates that in this scenario there are no subscribers. However, both providers occasionally offer high subscription rates as indicated in Fig. 4.10a. This happens because providers believe that by adjusting the subscription rates they can affect the blocking probability of the card service and thus achieve higher revenue. However, the revenue is not affected as indicated by the Fig. 4.10c.

P-R: only-subscriber market

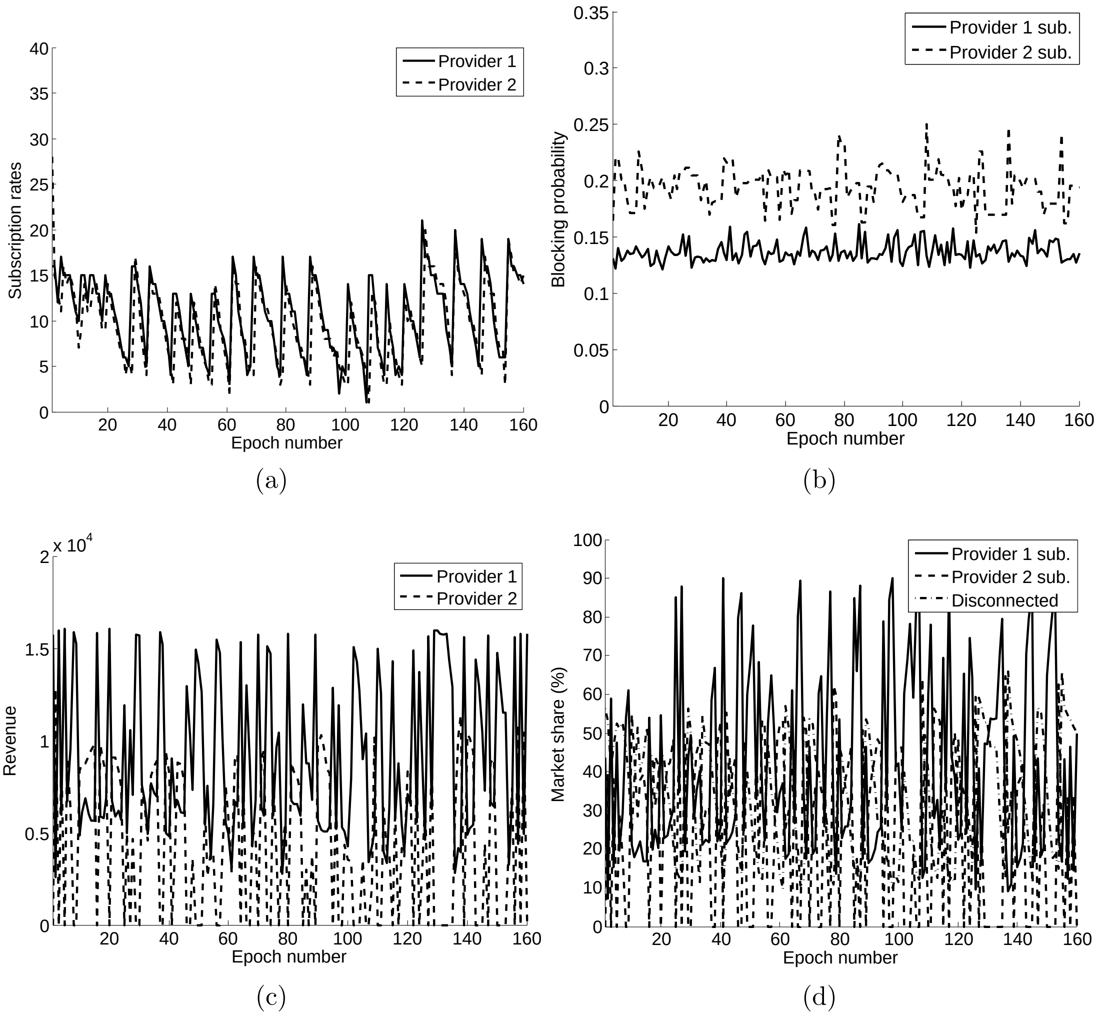


Figure 4.11: P-R only-subscriber market: subscription rates (a), blocking probability (b), revenue of providers (c), market share (d)

Price preference in service selection triggers an intense competition between providers. Despite the advantage of the first provider with respect to the blocking probability (Fig. 4.11b), the subscription rate is the parameter that mostly influences the user decisions. This results in price-war like phenomena, in which both providers offer similar prices. Specifically, each provider offers a slightly lower price than its competitor to achieve higher revenue (Fig. 4.11a). This results in large movements of users between the two providers (Fig. 4.11d) and bursty time series of revenue (Fig. 4.11c).

P-R: mixed market

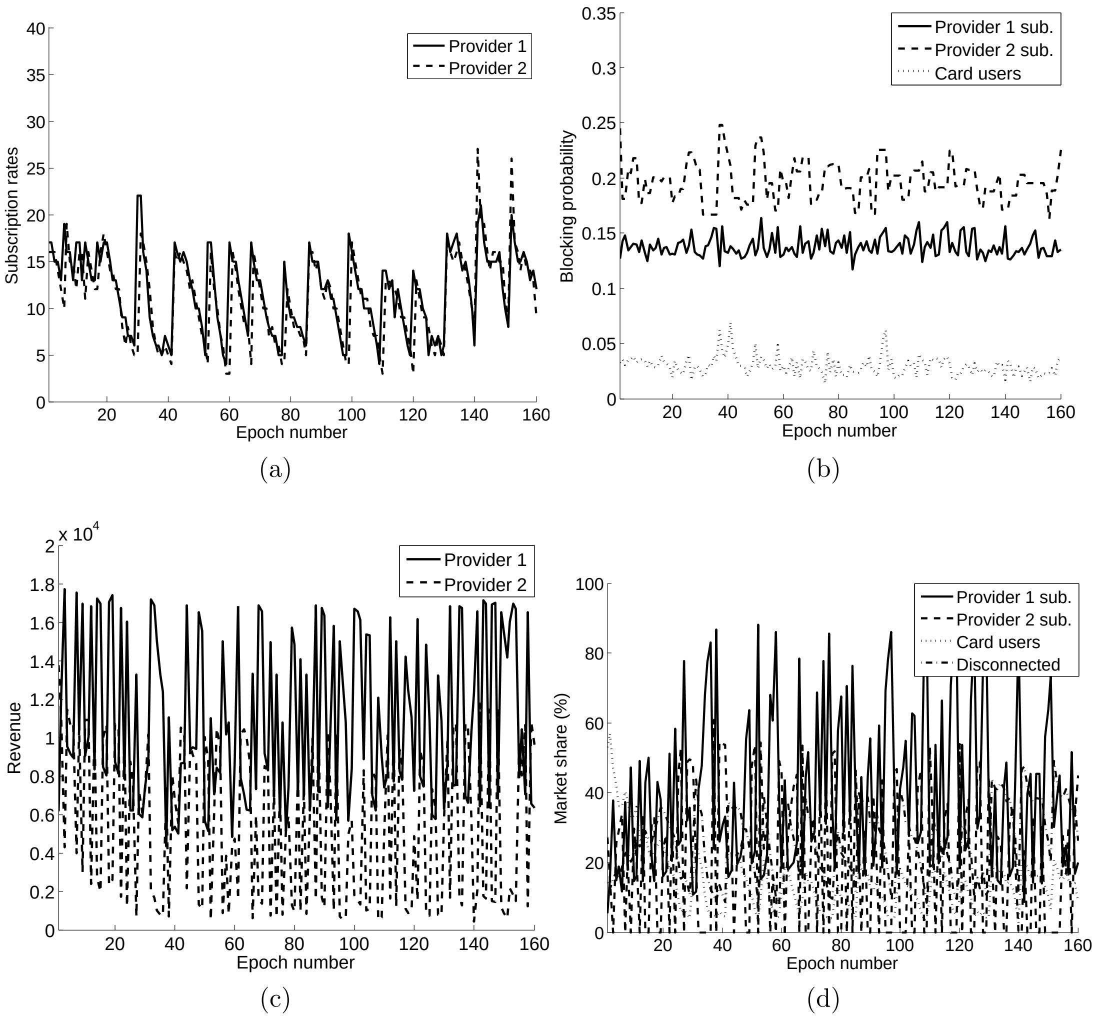


Figure 4.12: P-R mixed market: subscription rates (a), blocking probability (b), revenue of providers (c), market share (d)

In this scenario, the presence of the card service reduces the intensity of competition between providers leading to slightly higher subscription rates compared to the only-subscriber market. Specifically, each provider does not intend to reduce its price below a certain threshold, because by doing so, it will lose profit from the card users. Despite this fact, we can still observe price-war like phenomena, but the subscription rates are on average higher compared to the only-subscriber market (Fig. 4.12a vs 4.11a) leading to increased revenue for both providers (Fig. 4.12c vs 4.11c).

P-P: only-subscriber market

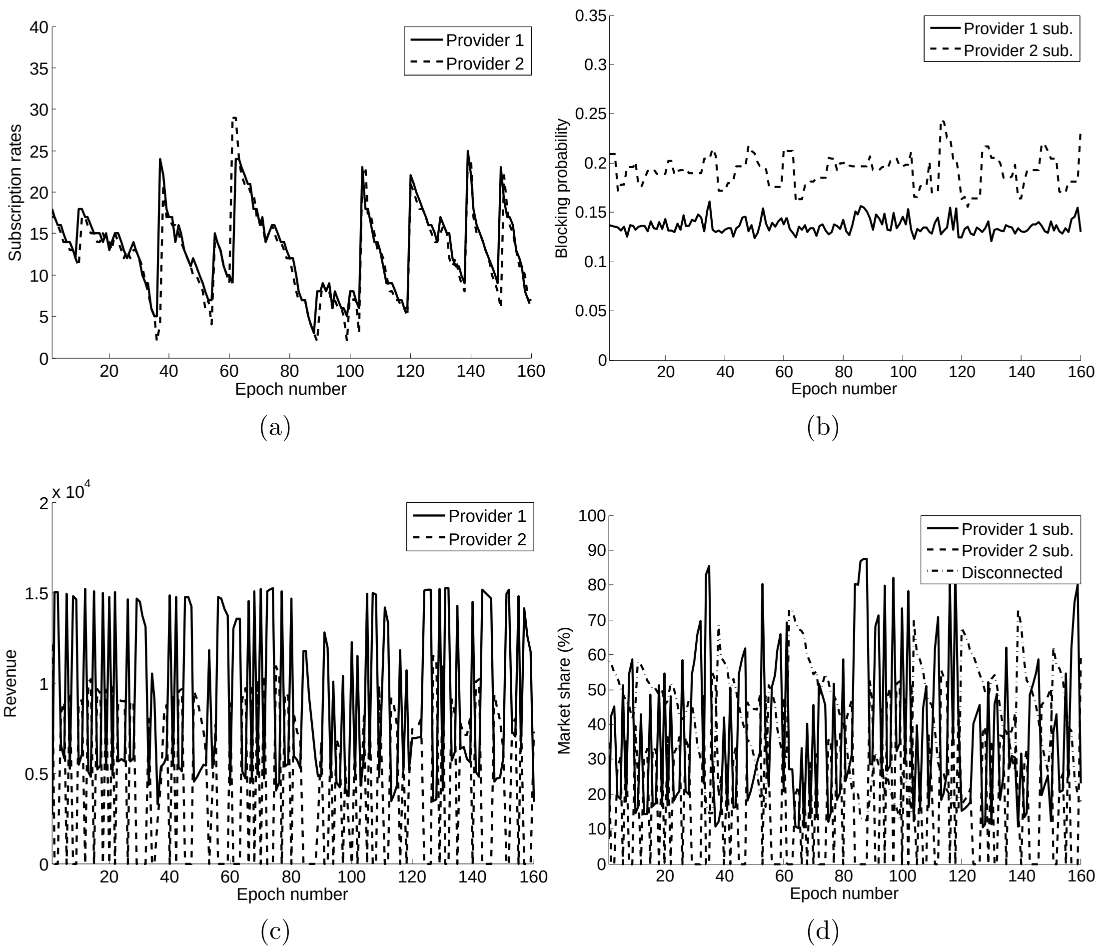


Figure 4.13: P-P only-subscriber market: subscription rates (a), blocking probability (b), revenue of providers (c), market share (d)

In this scenario, we observe similar trends compared to the only-subscriber market in P-R. This is expectable, because the price preference in the BS selection affects only the decisions of users that exceed their free time. Users that have not surpassed their free time, pay only the subscription rate which means that the cost of their calls does not depend on the transmission power they invest. Thus, they tend to invest the maximum allowable transmission power to achieve high data-rate. When users surpass their free time, they are charged proportionally to the transmission power they invest and the price preference in BS selection can significantly affect their decision. The differences that we observe in the only-subscriber market between the P-R and P-P scenarios are due to this phenomenon.

P-P: mixed market

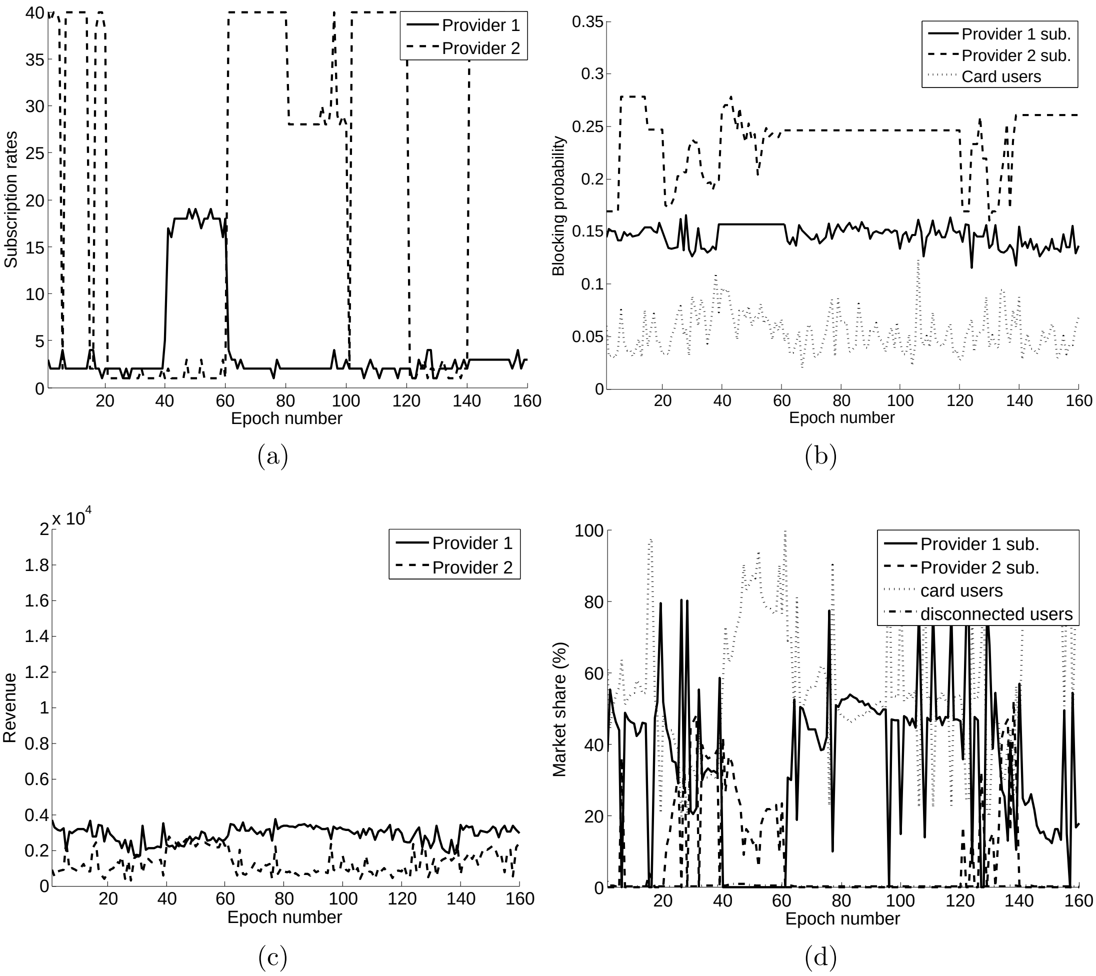


Figure 4.14: P-P mixed market: subscription rates (a), blocking probability (b), revenue of providers (c), market share (d)

Fig. 4.14a indicates that the provider 2 offers regularly a very high subscription rate. This is due to the sigmoid model which makes the provider 2 believe that if it increases its subscription rate, it will improve the blocking probability of the card service. Specifically, in cases that the provider 2 cannot achieve additional revenue by lowering its subscription rate, to attract more subscribers, it may instead increase the subscription rate to decrease the blocking probability of the card users. However, as shown in Fig. 4.14b, this choice of the provider 2 does not significantly affects the blocking probabilities and the provider 2 achieves lower revenue.

4.2.2.4 Discussion on sensitivity analysis with respect to the user profiles

An important question in this study, is how the characteristics of the user population affect the performance of the market (e.g., the blocking probability, percentage of disconnected users, and revenue of providers). We expect that, an increase of the user willingness to pay would not significantly affect the observed blocking probability and percentage of disconnected users. This is due to the price-setting mechanism of providers, which will increase the subscription and card rates to take advantage of the increased user willingness to pay. On the contrary, the increased prices will result in an increase of the revenue of providers. Moreover, we expect that the increase of the revenue will be more intense in scenarios with blocking probability and rate preference (B-R) compared to s scenarios with price preference (P-P). This is due to the intense price competition of providers in scenarios in which users are characterized by price preference.

We also expect that, a decrease in the blocking probability threshold of users will result in an increase of the percentage of disconnected users and a small decrease of the blocking probability. This is due to the strong dependency of the observed blocking probability to the willingness to pay and target rate thresholds of users. The effect of the channel availability on the blocking probability is less intense due to the small user demand which is on average lower that the channel availability of providers.

An increase in the data-rate threshold of users will result in fewer users being able to satisfy their thresholds and thus, in an increase of the observed blocking probabilities and percentage of disconnected users. Moreover, in scenarios with rate preference in the BS selection (B-R and P-R), we expect that the offered prices would not be significantly affected by the increase of the rate threshold. This is due to the strong dependency of the offered rices to the user willingness to pay thresholds in such scenarios. In addition, the increased percentage of disconnected users and blocking probability will result in a decrease of the revenue of providers. In scenarios with price preference in the BS selection (B-P and P-P), we expect that the increased rate threshold of users will reduce the intensity of competition between providers. Specifically, users will have fewer choices of BSs to satisfy their rate requirement, and thus, they will tend to select the closest BS. This will give the opportunity to providers to increase their prices and achieve a higher revenue. Such results have already been observed in the analysis presented in Section 3.3.2.2.

Finally, an increase of the average user demand beyond the channel availability of providers will result in an increase of the blocking probability. This increase will be more intense for the subscribers of provider 2 compared to provider 1. Moreover, we expect to observe an increased percentage of disconnected users. In scenarios with blocking probability preference in service selection (B-R and B-P), we expect to observe a small increase of the offered prices due to the increased demand, which will result in a small increase of the revenue of providers. On the contrary, in scenarios with price preference in the service selection (P-R and P-P), we expect that the increased user demand will decrease the intensity of competition between providers. Specifically, even if a provider is more expensive than its competitor, it will still attract all the customers that cannot be served by its rival provider due to the limited channel availability. This will give the opportunity to provider to increase their prices and achieve higher revenue compared to scenarios with small user demand. Appendix B provides the results of a sensitivity that was performed in order to evaluate the above conclusions.

Chapter 5

Conclusions

This thesis presents a modeling framework and simulation platform that allow us to instantiate and assess various types of access markets. This framework takes into consideration various parameters, such as, the channel, the network topology, the network operator infrastructure deployment/distribution, the user mobility and distribution, the relations and interactions among providers and users, the multiple spatio-temporal scales (over which these relations and interactions are manifested), the type, reliability and amount of information that is available to various entities, the user preferences and tolerance criteria with respect to the wireless access (e.g., based on transmission rate, energy, financial cost) and the provider selection mechanism, the user profile, the utility functions of the providers, and price-adaptation algorithm. It also considers a diverse set of customer populations and analyzes the evolution of the market using metrics that can provide insight to regulators, customers, and operators.

It proposes the "u-map", a novel system with a user-centric geo-database that enables users to upload measurements that their devices collect about network conditions, interference, and coverage as well as their feedback about their profile and QoE for certain types of services. The analysis shows that 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 parameters to improve their targets. Finally, it introduces the "flexi-card" service, which becomes a catalyst, providing significant benefits, compared to traditional markets with only subscribers. The analysis demonstrates that the duopoly that offers the card services in addition to subscriptions alleviates the market exclusion effects, dramatically reduces the percentage of disconnected users, and decreases substantially the blocking probabilities. Furthermore, due to the larger participation in the market, the social welfare attained is also substantially improved, thus comprising further evidence of the merits of having the multiple product offerings in the market.

Chapter 6

Future work

We plan to experiment with tit-for-tat price adaptation strategies and investigate whether the two providers can implicitly cooperate to offer prices that yield higher revenue to both, instead of constantly competing against each other. The analysis will be extended to include a sensitivity analysis of the various thresholds and multiple degrees of asymmetry of the two providers (in terms of deployment and resources). Another important long-term objective of this research is the incorporation of measurements from a real-life network environment in our simulation platform. Specifically, we consider the integration of information collected from a metropolitan-area wireless network, e.g., BSs deployment, empirical-based channel models (e.g., ray-tracing), mobility models, and user traffic traces. This will further enrich the simulation platform by enabling the cross-validation and analysis of various paradigms and spectrum markets in even more realistic settings. We also plan to incorporate the presence of malicious, mis-configured or non-rational entities in our simulation platform. For example, malicious/mis-configured clients may upload erroneous information on the u-map, while non-rational entities can make "mistakes".

Another research direction is to enhance the price setting algorithm with longer-term objectives, define a more sophisticated blocking probability prediction model, and reservation policies that can be superior to myopically greedy approaches. Specifically, we will explore a longer time scale prediction of the users' reaction to the posted prices and more importantly the competitor's reaction curve. Furthermore, we will employ state-of-the-art "trunk reservation" policies for reserving a part of the network for the high-value high-business users, thus offering competitive prices and attractive blocking probabilities.

In this thesis the modeling of spectrum markets is performed at a microscopic level and considers the distinct characteristics of all users and providers. This methodology is accurate but becomes computationally intractable especially in cases of large markets. On the other hand, macroscopic approaches that have been proposed in the literature are more tractable but their results may be highly inaccurate in certain cases. For example, an average metric that describes the user profiles may not be able to capture the spatial variations of the user behavior and demand. Specifically, not only in different regions we may have distinct customer profiles, but also a certain customer may exhibit different behavior depending on the region in which it is located. For example, customers at the center of a metropolitan area may have higher traffic demand while at the suburbs, their wireless demand may decrease (e.g., due to the use of wired infrastructure). Moreover, a mobile user depending on its content may have different traffic demand characteristics. Finally, different channel conditions depending on the region may impose different radio propagation characteristics and affect the channel quality and the offered services.

A long-term goal of this research is to propose a methodology to perform appropriate aggregations of the entities at the microscopic level that will reduce the computational complexity and at the same time control the loss of information, taking into consideration the aforementioned parameters. Specifically, we plan to introduce various levels of detail between the microscopic and macroscopic levels, each with different amount of available information and complexity. These levels of detail are called "mesoscopic levels" and we can choose among them depending on the phenomenon which we need to analyze. One way to define the mesoscopic levels would be to apply different data-mining and clustering algorithms to define "representative entities". The representative entities will be fewer compared to real entities reducing the computational complexity and at the same time they will describe the behavior of real entities in a more accurate manner compared to simple averages.

Appendix A

Simulation platform functions

Table A.1 provides a brief description of the matlab functions that implement the simulation platform and describes how these functions call each other.

Table A.1: **Matlab functions**

Function	**Description**	**Calls**	**Called by**
Construct_topology	Constructs the topology of the network	Providers_topology Users_topology	
Providers_topology	Constructs the network of BSs of providers		Construct_topology
Users_topology	Generates the population of users		Construct_topology
Monte_Carlo	Performs multiple random realizations (Monte Carlo runs) of an experiment	Define_cells Define_representatives Nominated_devices Run_experiment	
Define_cells	Divides a region into a number of subregions and classifies users according to the subregion in which they belong		Monte_Carlo
Define_representatives	Defines the characteristics of the representative users in each subregion	Divide_set	Monte_Carlo Run_experiment

Divide_set	Distributes a resource among M entities according to a probability vector p		Define_representatives Run_experiment
Nominated_devices	Finds the BSs and users that lie in the region of interest		Monte_Carlo Present_results
Run_experiment	Performs a single realization of a given time interval of the experiment	Experiment_schedule Secondary_utility Subscriber_utility Estimate_interference Find_cell Apriori_utility Primary_utility Least_squares Logit Metropolis update_price plot_topology Define_representatives	Monte_Carlo
Experiment_schedule	Constructs a schedule of all the events that will take place during an interval of the experiment	User_schedule	Run_experiment
User_schedule	Returns the time instances that mark the beginning and end of user calls as well as the ids of users that performed these calls	Call_durations Inter_call_durations	Experiment_schedule
Call_durations	Draws random samples for the call durations of users		User_schedule
Inter_call_durations	Draws random samples for the inter-call intervals of users		User_schedule Run_experiment
Secondary_utility	Computes the utility of a card user for all available strategies	Channel_model	Run_experiment Run_experiment
Channel_model	Computes the channel gain from a user position to a given set of BSs using the Okumura-Hata path loss model		Secondary_utility Subscriber_utility Estimate_interference Representative_utility Average_interference

Subscriber_utility	Computes the utility of a subscriber user for all available strategies	Channel_model	Run_experiment Subscriber_utility Estimate_interference Representative_utility
Estimate_interference	Estimates the interference that is introduced by the transmission of a specific user to various BSs	Channel_model	Run_experiment
Find_cells	Maps a user position in the considered geographical region to a specific subregion		Run_experiment
Apriori_utility	Estimates the utility of a provider for all possible prices it can offer. This estimation is performed using the method of the representative users	Representative_utility Average_interference	Run_experiment
Representative_utility	Computes the utility of a representative user for all available strategies	Channel_model Inter_call_durations	Apriori_utility
Average_interference	Updates the data structure that stores the average interference at each BS	Channel_model	Apriori_utility
Primary_utility	Measures the utility that is achieved by each provider a posteriori. This method of utility estimation is used in the polynomial approach		Run_experiment
Least_squares	Fits a polynomial of second degree to a Dataset. The Hessian of this polynomial is positive semi-definite		Run_experiment
Logit	Implements the Logit rule		Run_experiment

Metropolis	Implements the Metropolis algorithm		Run_experiment
update_price	Applies a gradient-based rule to update the offered price of a service provider in the case of the polynomial approach		Run_experiment
plot_topology	Plots a snapshot of the network topology		Run_experiment
Shadowing_matrix	Determines the contribution of shadowing to the channel gain at the positions of BSs		Construct_topology
Present_results	Processes the data structure in which we store the results of an experiment. It produces various plots and returns It performance statistics for providers, card, and subscriber users	Nominated_devices	

To run an experiment the following steps should be performed:

1. **Construct the topology of the network**: Specify the values of all the input parameters of the function Construct_topology and call this function. That way the data structures PD (provider BSs) and SD (user population) will be produced. Subsequently one should execute the function Shadowing_matrix with the proper input to determine the contribution of shadowing to the channel gain at the positions of BSs.

2. **Run the experiment**: After producing the data structures PD, SD and S from the previous step one should specify the values of all the remaining required input parameters of the function Monte_Carlo and execute this function.

3. **Present the results of the experiment**: Load the file which contains

the data structure with the results of the experiment. Then execute the function Present_results to compute performance statistics for the providers and users and produce plots.

Appendix B

Sensitivity analysis

To evaluate the effect of the user characteristics on the performance of the market, we performed a sensitivity analysis study. In this study, we defined a baseline user case, in which the constraints of the users follow Gaussian distributions with parameters that are given in Table B.1.

Table B.1: **User constraints in the baseline user case**

Constraint	**Mean**	**Standard deviation**
Willingness to pay (service selection)	0.17	0.0374
Blocking probability	0.2	0.05
Willingness to pay (BS selection)	0.15	0.0374
Data-rate (Mbps)	0.1	0.01

Subsequently, we defined some additional user cases by changing, each time, the mean value of a specific user constraint. For example, in the *high willingness to pay* user case, we increased the mean value of the user willingness to pay, in the service and BS selection, from 0.17 and 0.15 Euros/min to 0.22 and 0.20 Euros/min respectively. In the *high target data-rate* user case, we increased the mean value of the user data-rate requirement from 0.1 Mbps to 0.12 Mbps. Finally, in the *low blocking probability threshold* user case, we decreased the mean value of the user blocking-probability threshold from 0.2 to 0.165. The parameters of the Gaussian distributions that determine the user constraints, in the aforementioned user cases, are shown in Tables B.2, B.3, B.4.

Table B.2: **User constraints in the high willingness to pay user case**

Constraint	Mean	Standard deviation
Willingness to pay (service selection)	**0.22**	0.0374
Blocking probability	0.2	0.05
Willingness to pay (BS selection)	**0.20**	0.0374
Data-rate (Mbps)	0.1	0.01

Table B.3: **User constraints in the high target data-rate user case**

Constraint	Mean	Standard deviation
Willingness to pay (service selection)	0.17	0.0374
Blocking probability	0.2	0.05
Willingness to pay (BS selection)	0.15	0.0374
Data-rate (Mbps)	**0.12**	0.01

Table B.4: **User constraints in the low blocking probability threshold user case**

Constraint	Mean	Standard deviation
Willingness to pay (service selection)	0.17	0.0374
Blocking probability	**0.165**	0.05
Willingness to pay (BS selection)	0.15	0.0374
Data-rate (Mbps)	0.1	0.01

As mentioned in Chapter 4, each user generates a sequence of call requests. In the baseline user case, the call duration follows a Pareto distribution ($x_s = 3.89$, $a = 4.5$) of mean 5 min, while the disconnection period follows a Log-normal distribution with different parameters for each user (μ is uniformly distributed in the interval [4.0679 6.2150] and σ is equal to 0.37) resulting in client demand varying from 33 to 267 minutes per epoch. To estimate the effect of the user demand on the performance of the market we defined the *high demand* user case, in which the parameter μ of the Log-normal distribution that corresponds to the disconnection periods is uniformly distributed in [3.3679 5.5150]. This results in client demand varying from 66 to 500 minutes per epoch. In the following sections we present performance evaluation results for all the aforementioned user cases.

B.1 Baseline user case

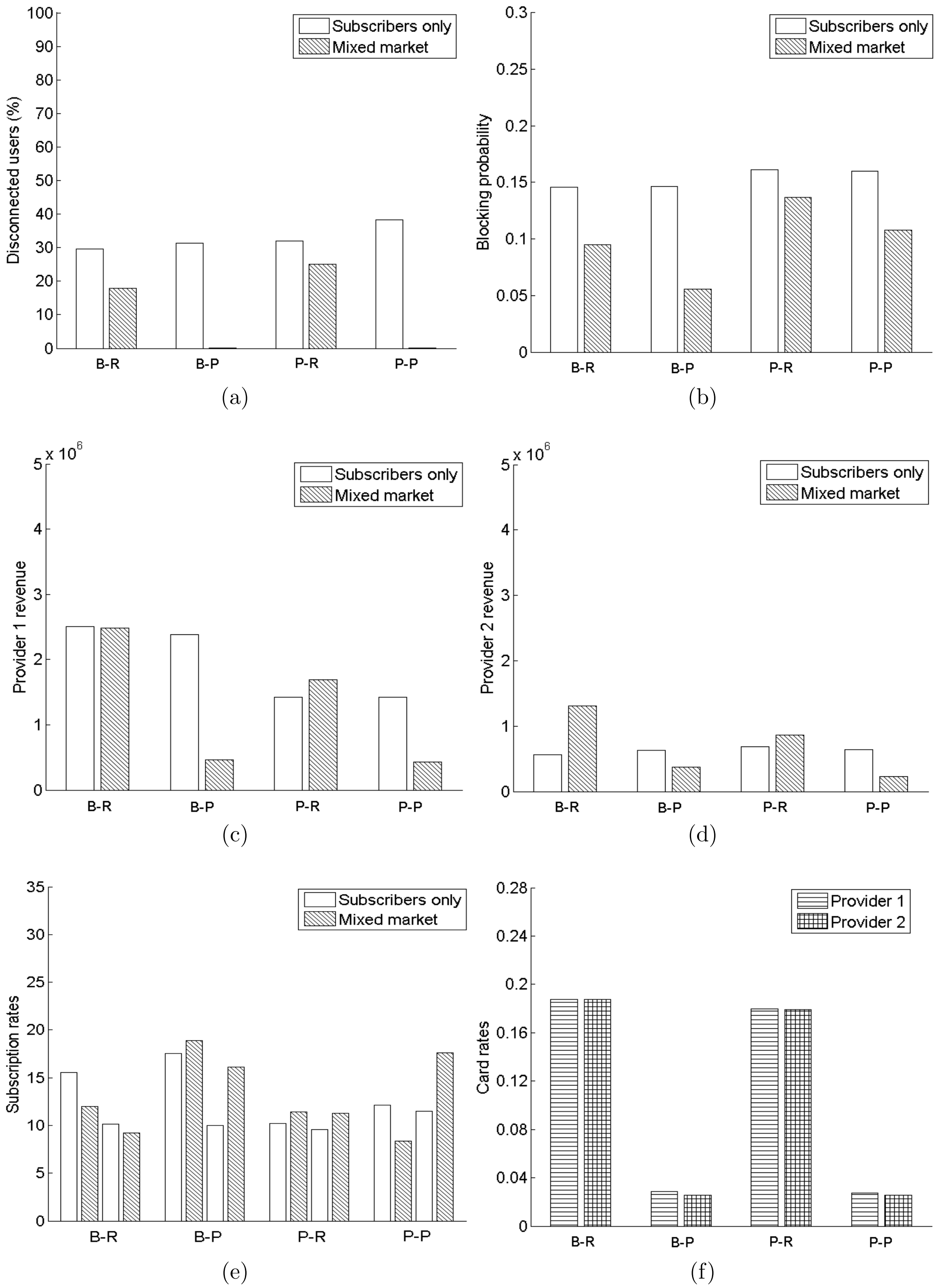


Figure B.1: (a) Percentage of disconnected users. (b) Blocking probability. (c), (d) revenue of providers. (e) Subscription rates. (f) Card rates.

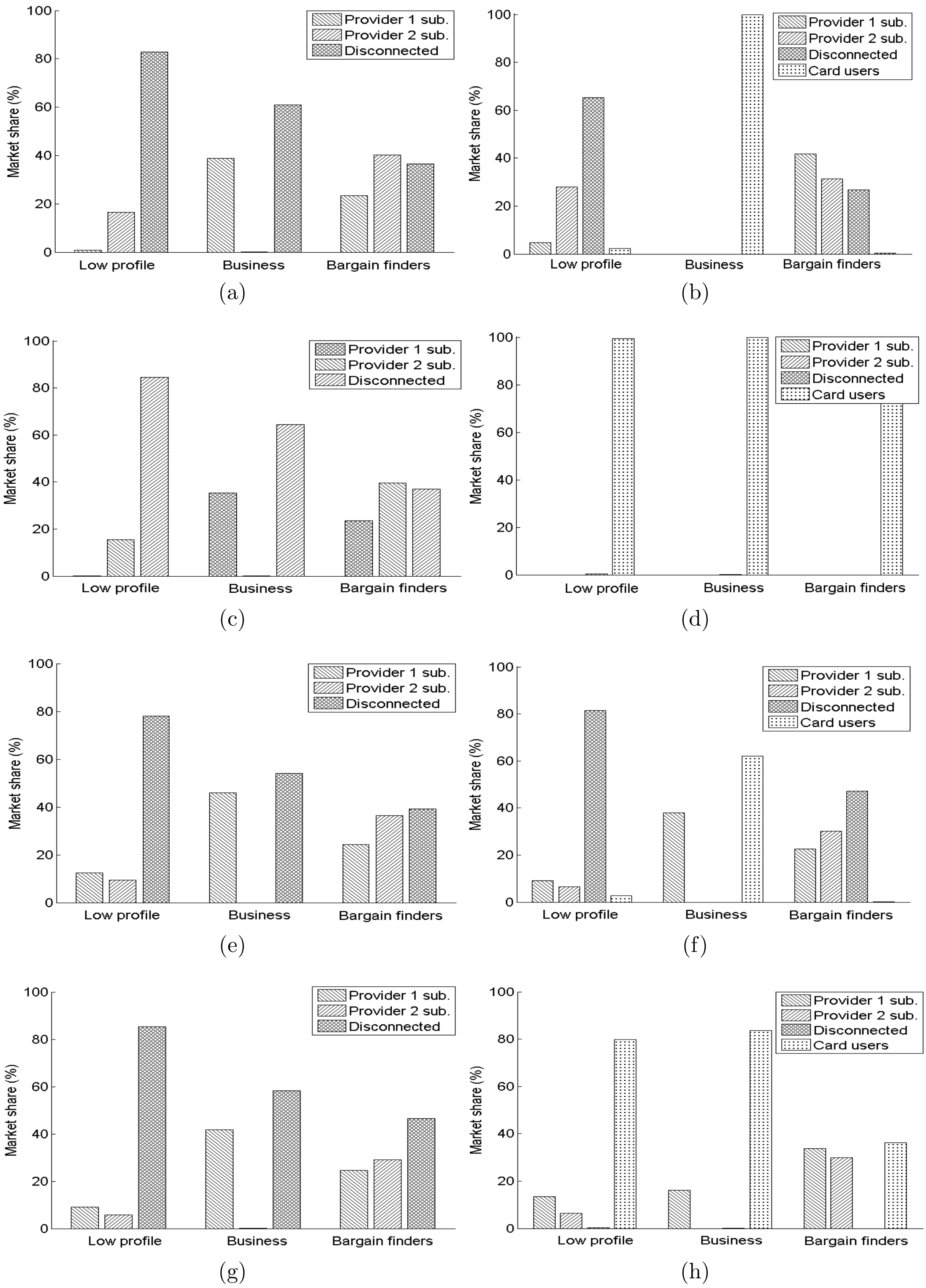


Figure B.2: **BR scenario**: only-subscriber market (a), mixed market (b). **BP scenario**: only-subscriber market (c), mixed market (d). **PR scenario**: only-subscriber market (e), mixed market (f). **PP scenario**: only-subscriber market (g), mixed market (h).

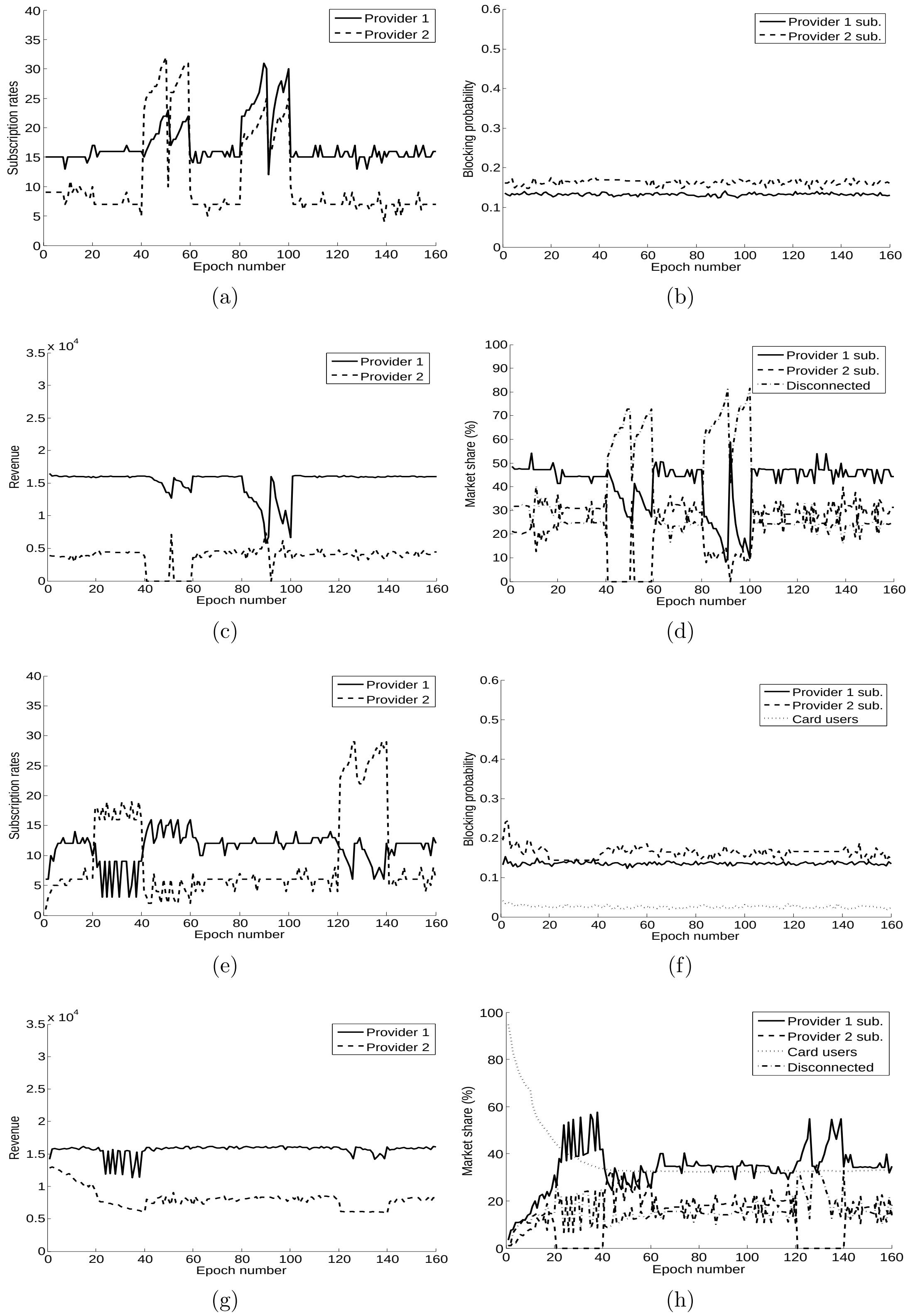


Figure B.3: BR scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

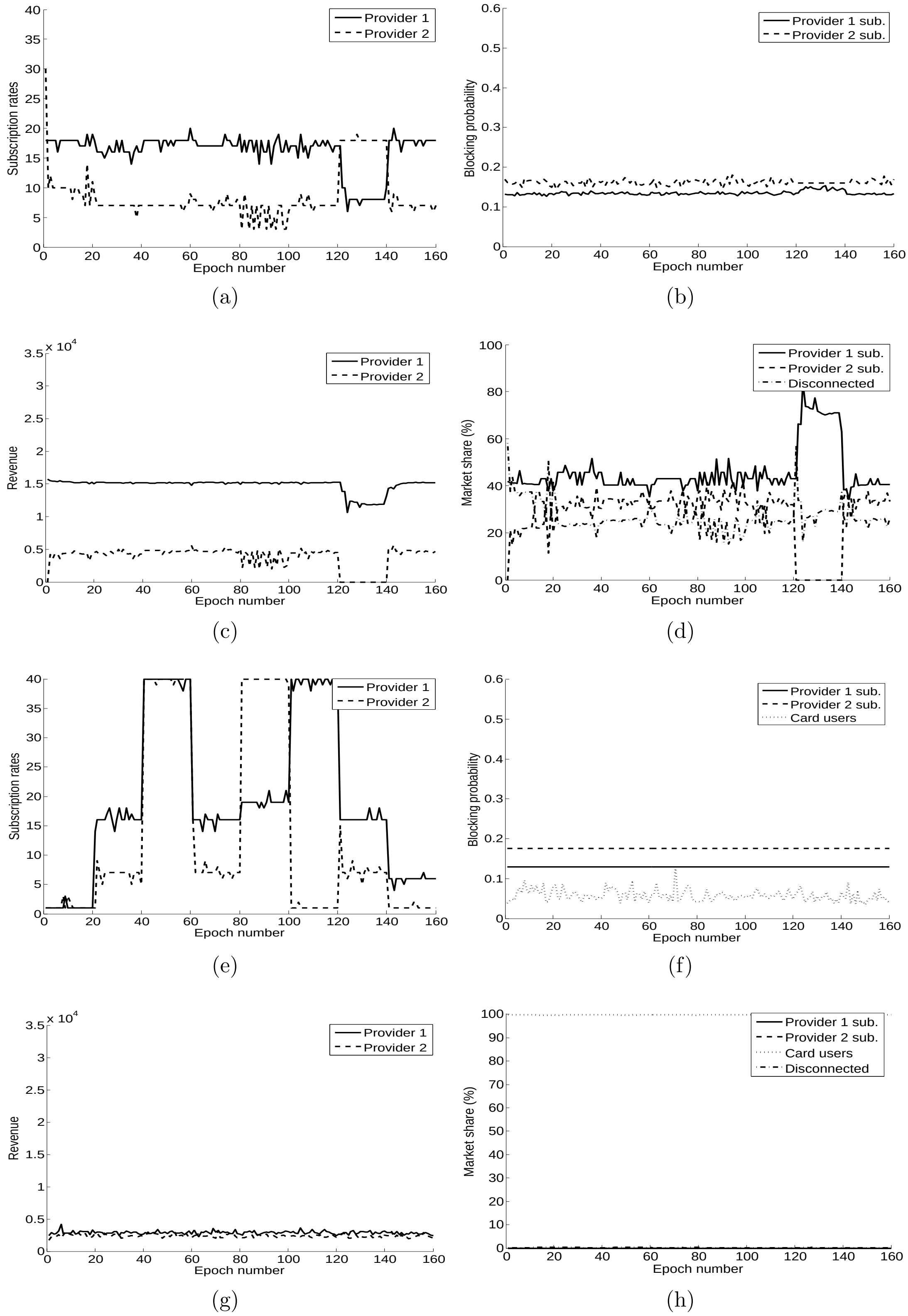


Figure B.4: BP scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

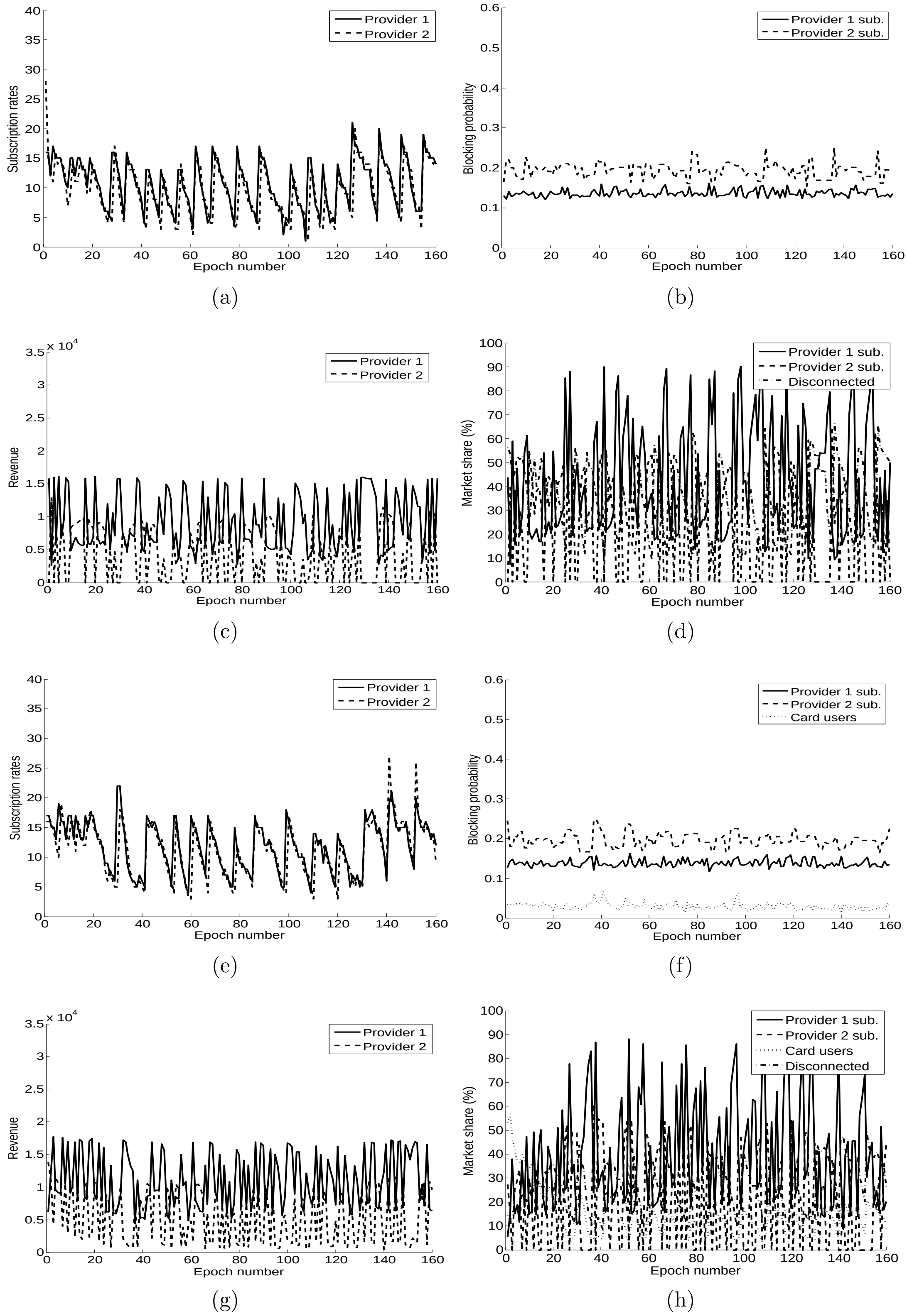


Figure B.5: PR scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

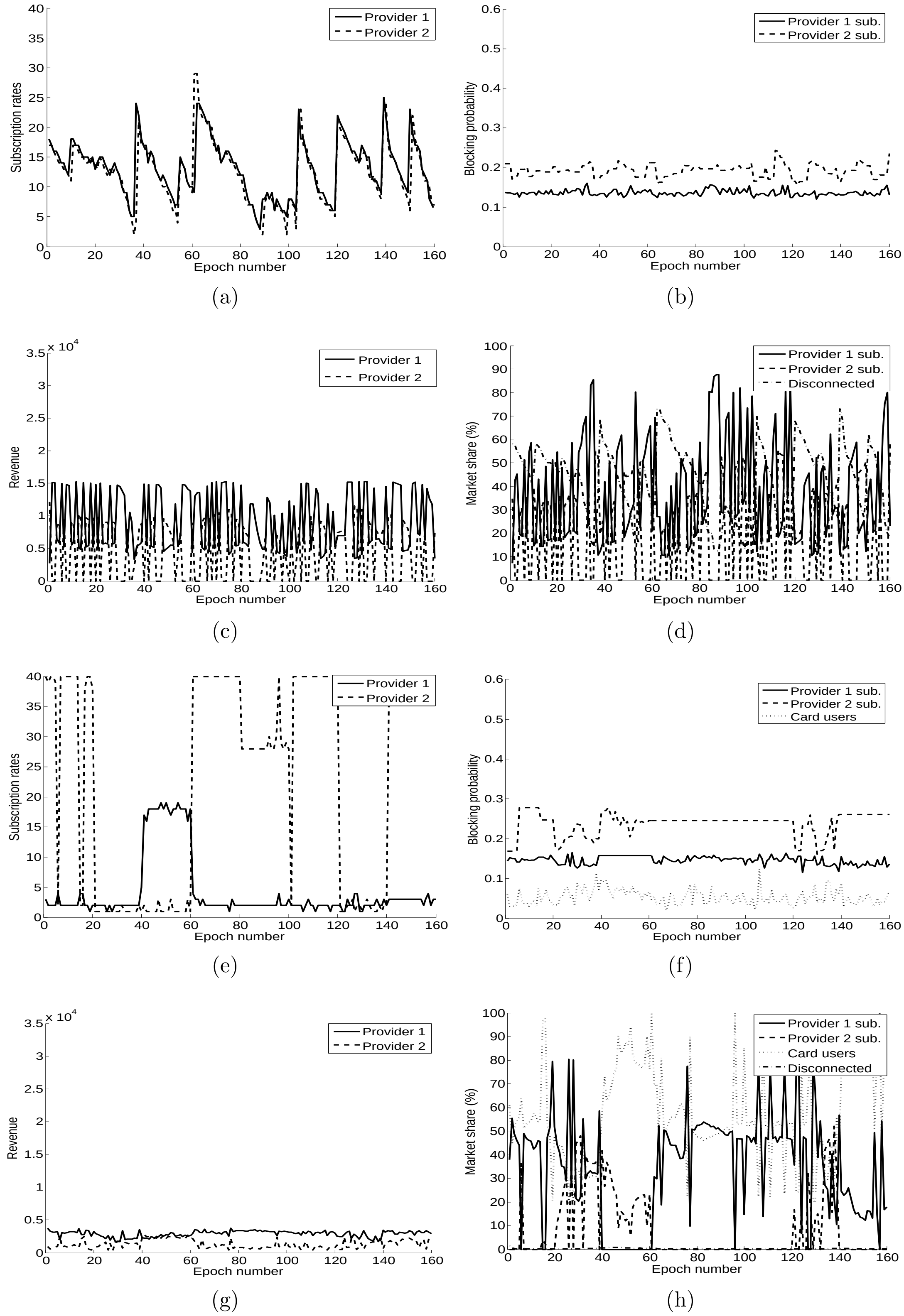


Figure B.6: PP scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

B.2 High willingness to pay

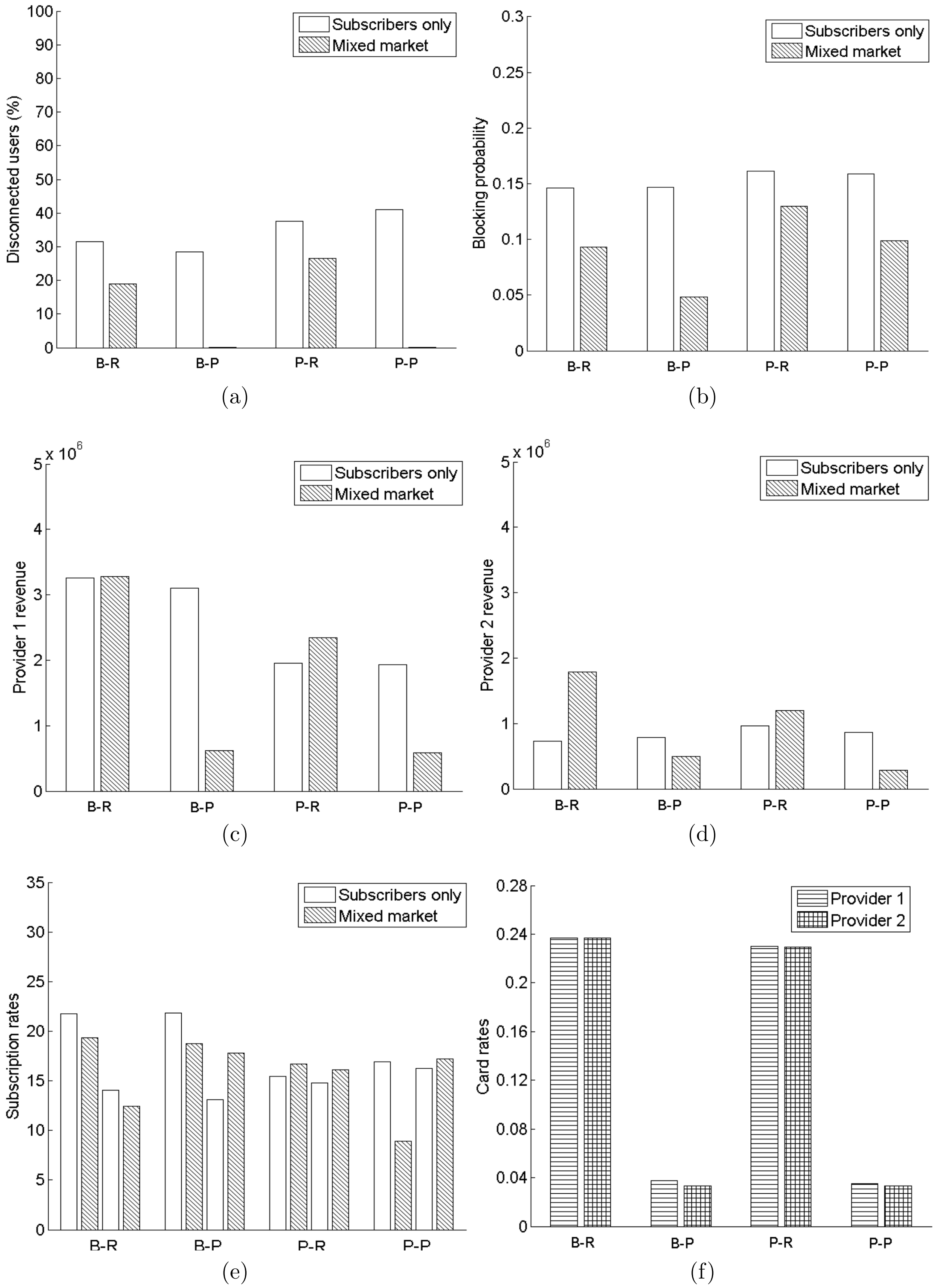


Figure B.7: (a) Percentage of disconnected users. (b) Blocking probability. (c), (d) revenue of providers. (e) Subscription rates. (f) Card rates.

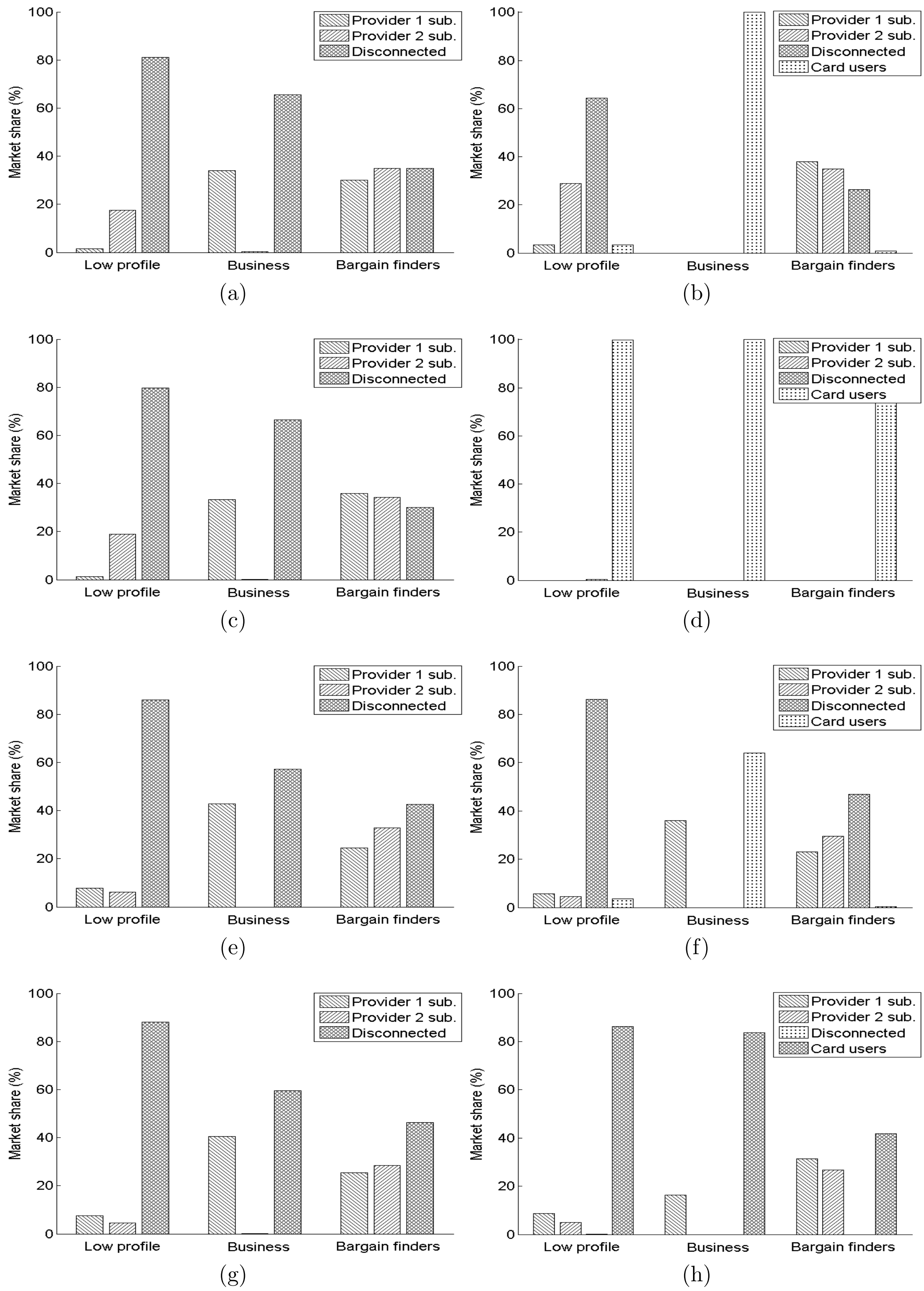


Figure B.8: **BR scenario**: only-subscriber market (a), mixed market (b). **BP scenario**: only-subscriber market (c), mixed market (d). **PR scenario**: only-subscriber market (e), mixed market (f). **PP scenario**: only-subscriber market (g), mixed market (h).

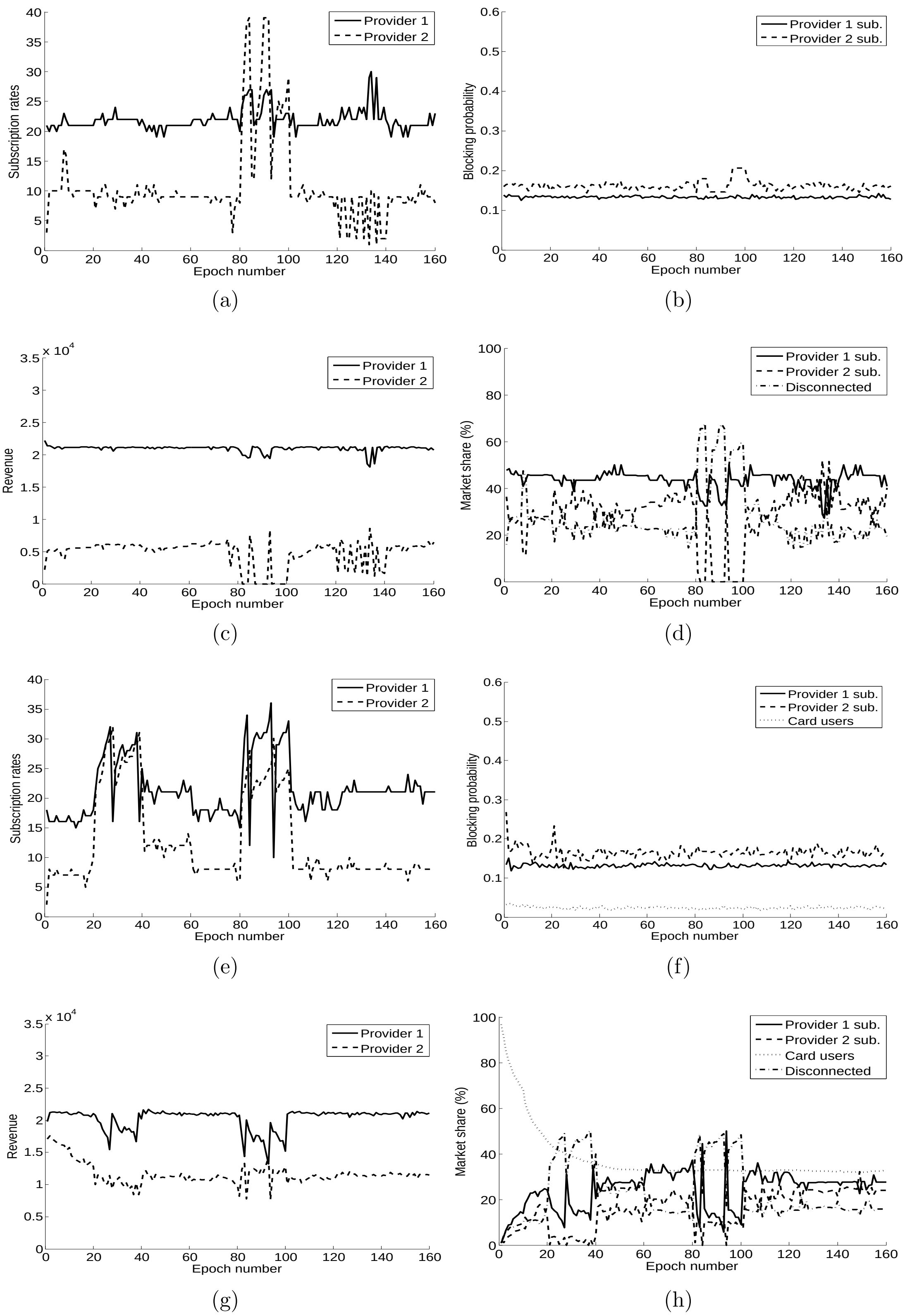


Figure B.9: BR scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

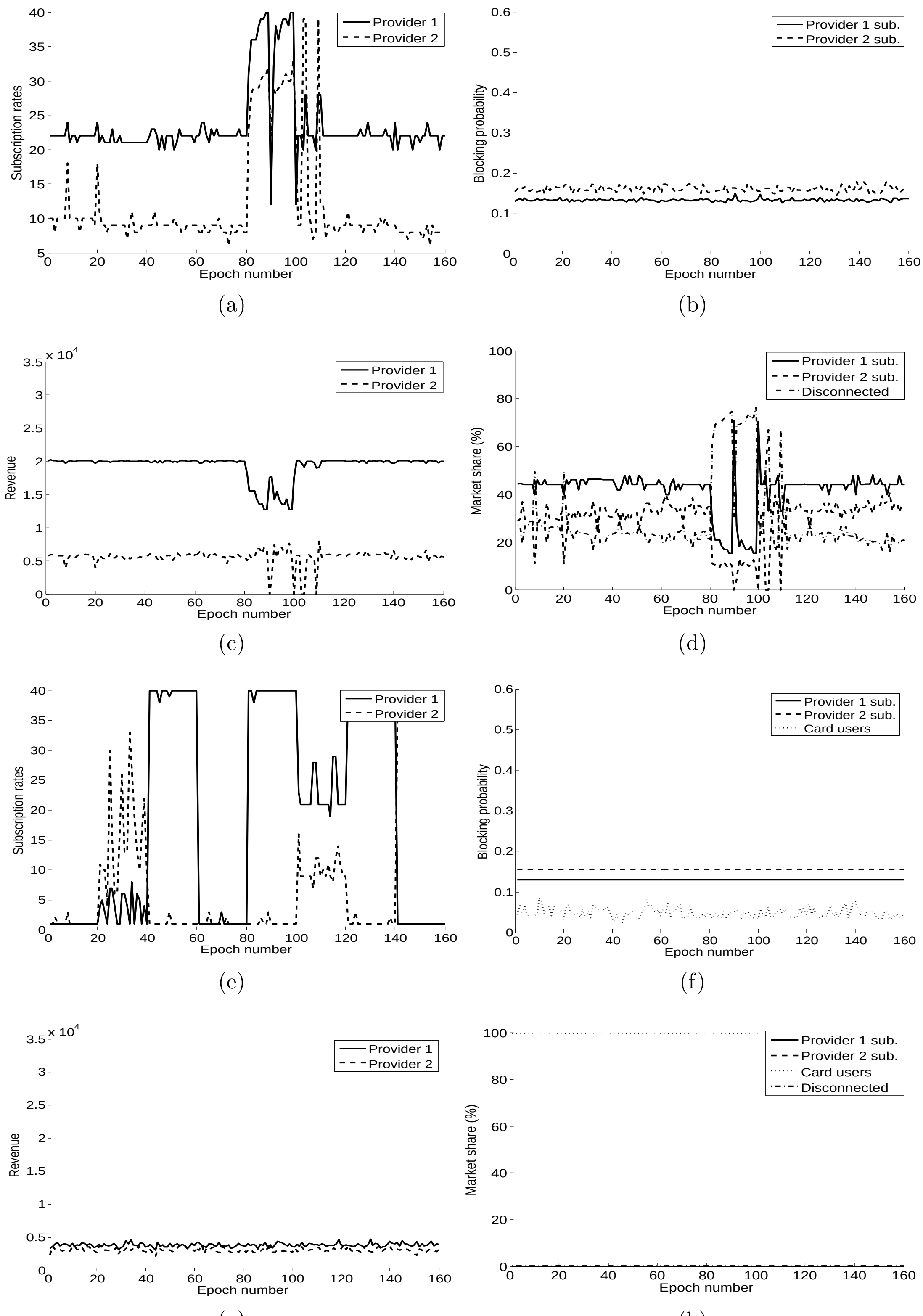


Figure B.10: BP scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

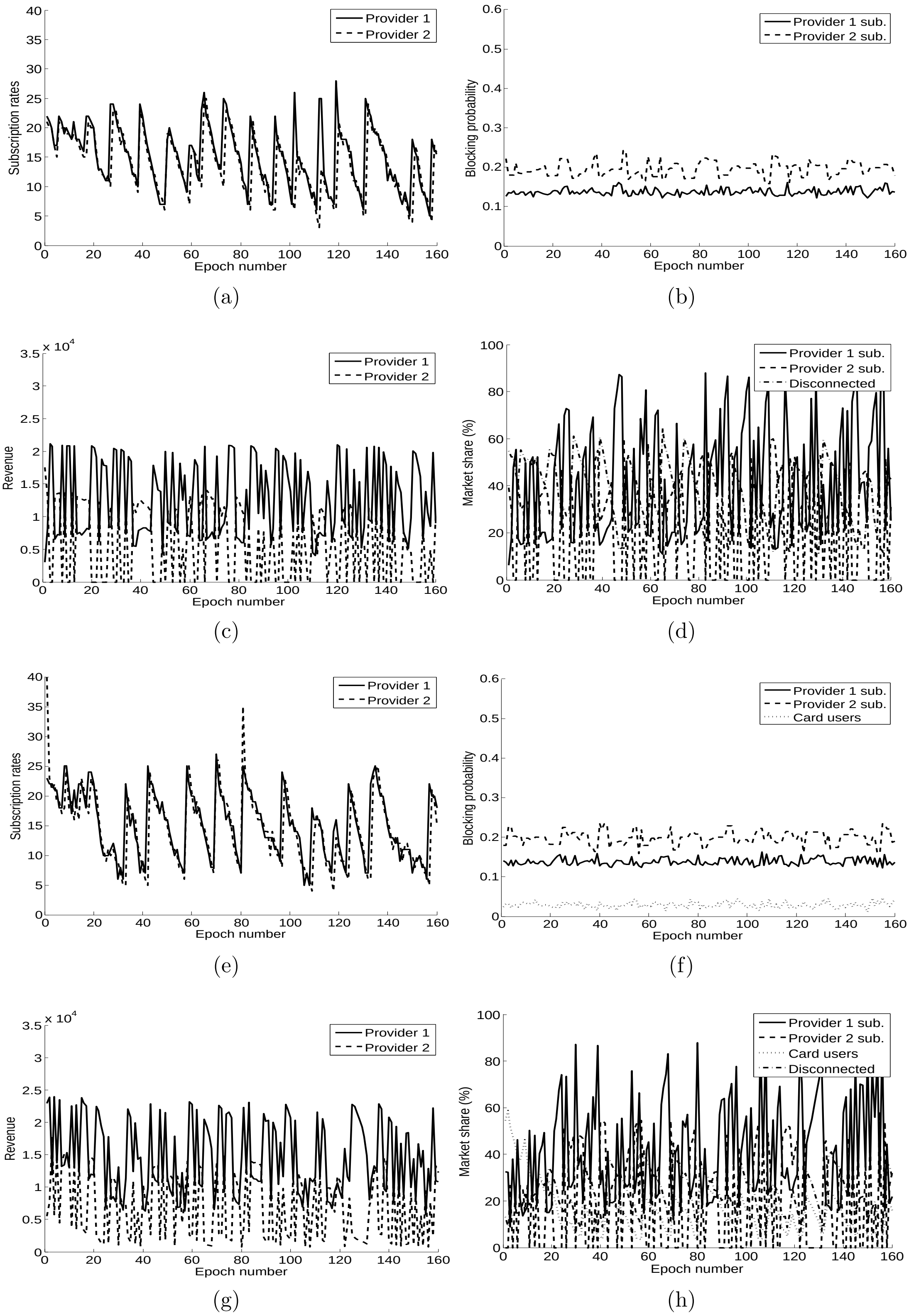


Figure B.11: PR scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

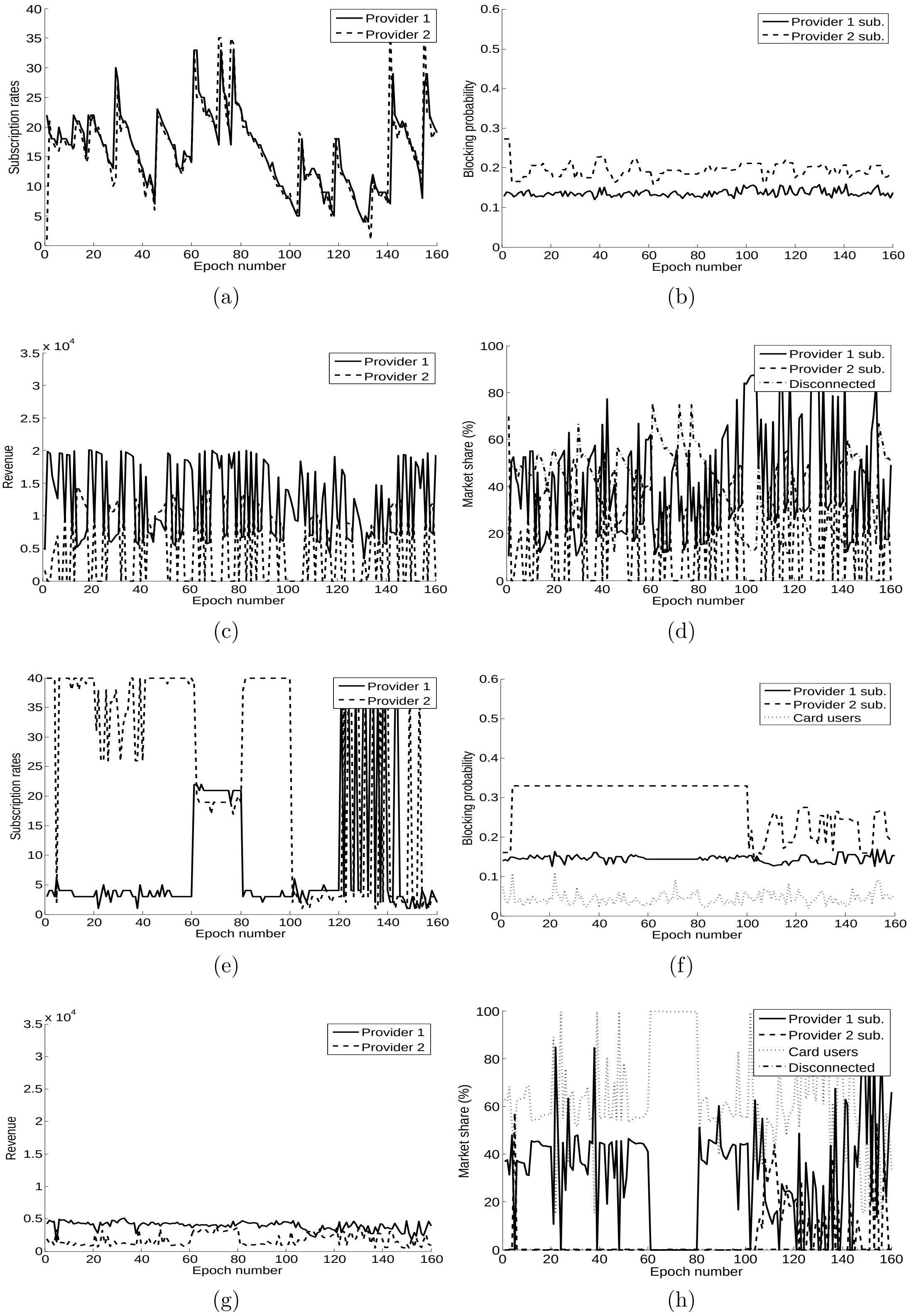


Figure B.12: PP scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

B.3 High target data-rate

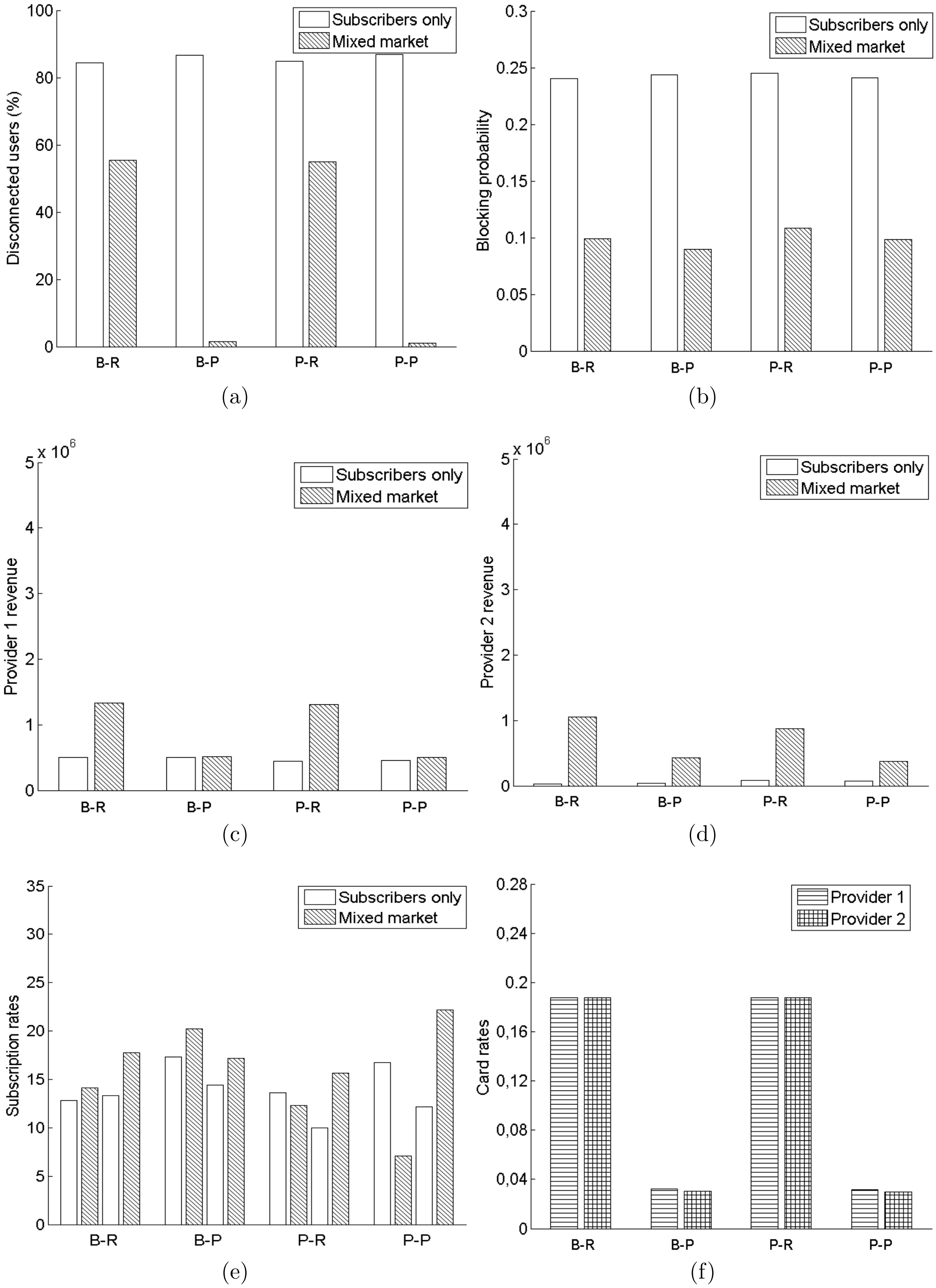


Figure B.13: (a) Percentage of disconnected users. (b) Blocking probability. (c), (d) revenue of providers. (e) Subscription rates. (f) Card rates.

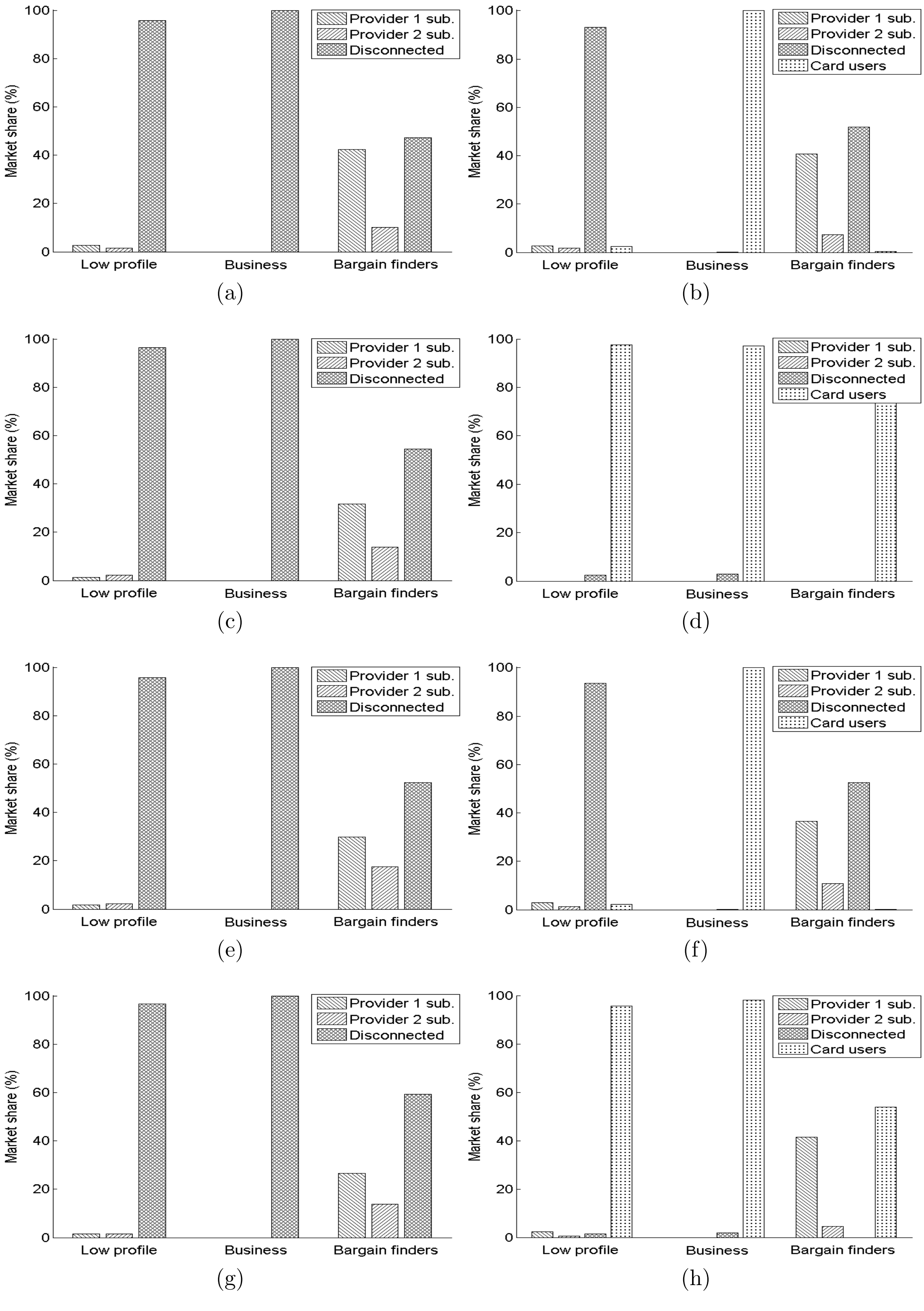


Figure B.14: **BR scenario**: only-subscriber market (a), mixed market (b). **BP scenario**: only-subscriber market (c), mixed market (d). **PR scenario**: only-subscriber market (e), mixed market (f). **PP scenario**: only-subscriber market (g), mixed market (h).

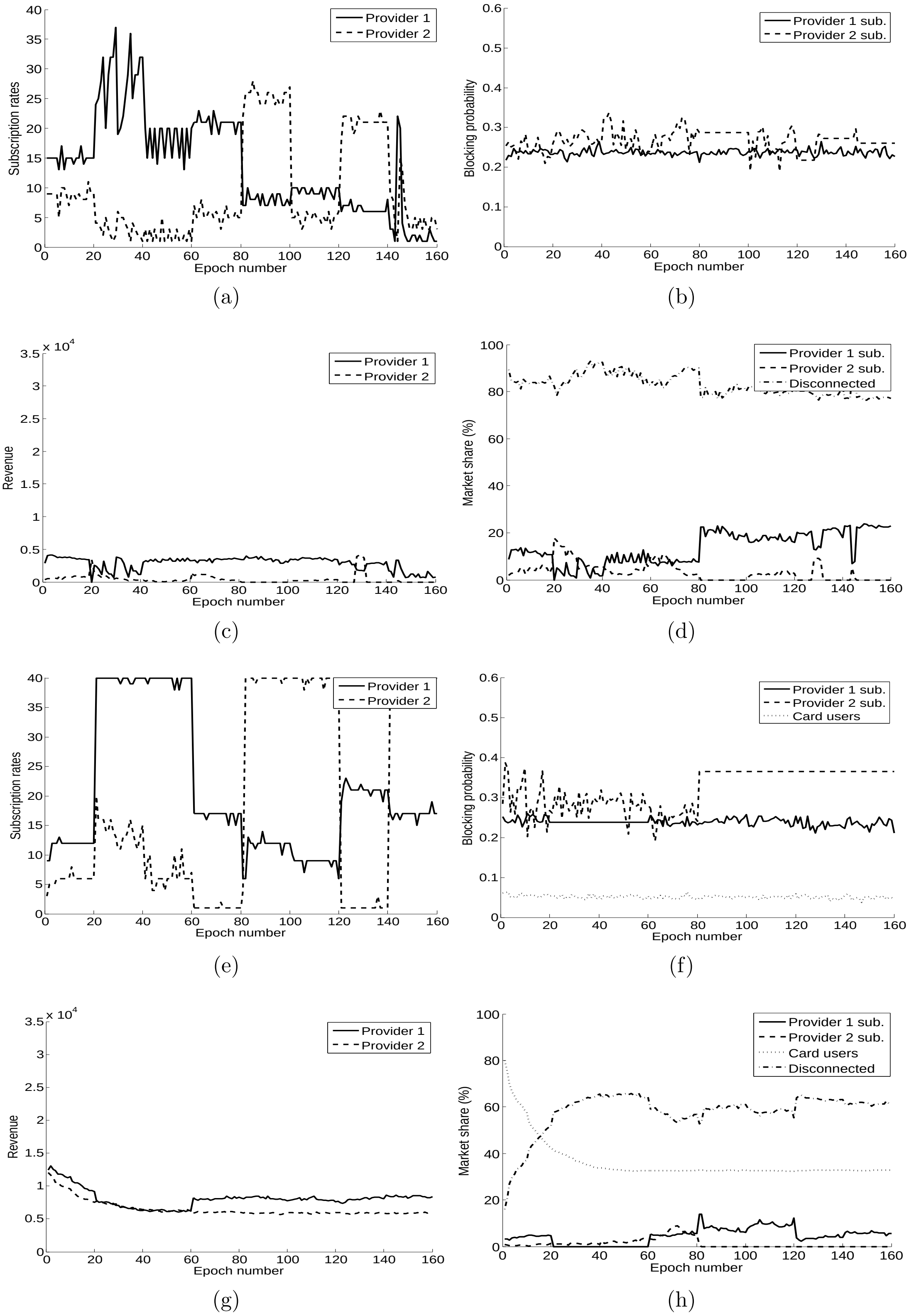


Figure B.15: BR scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

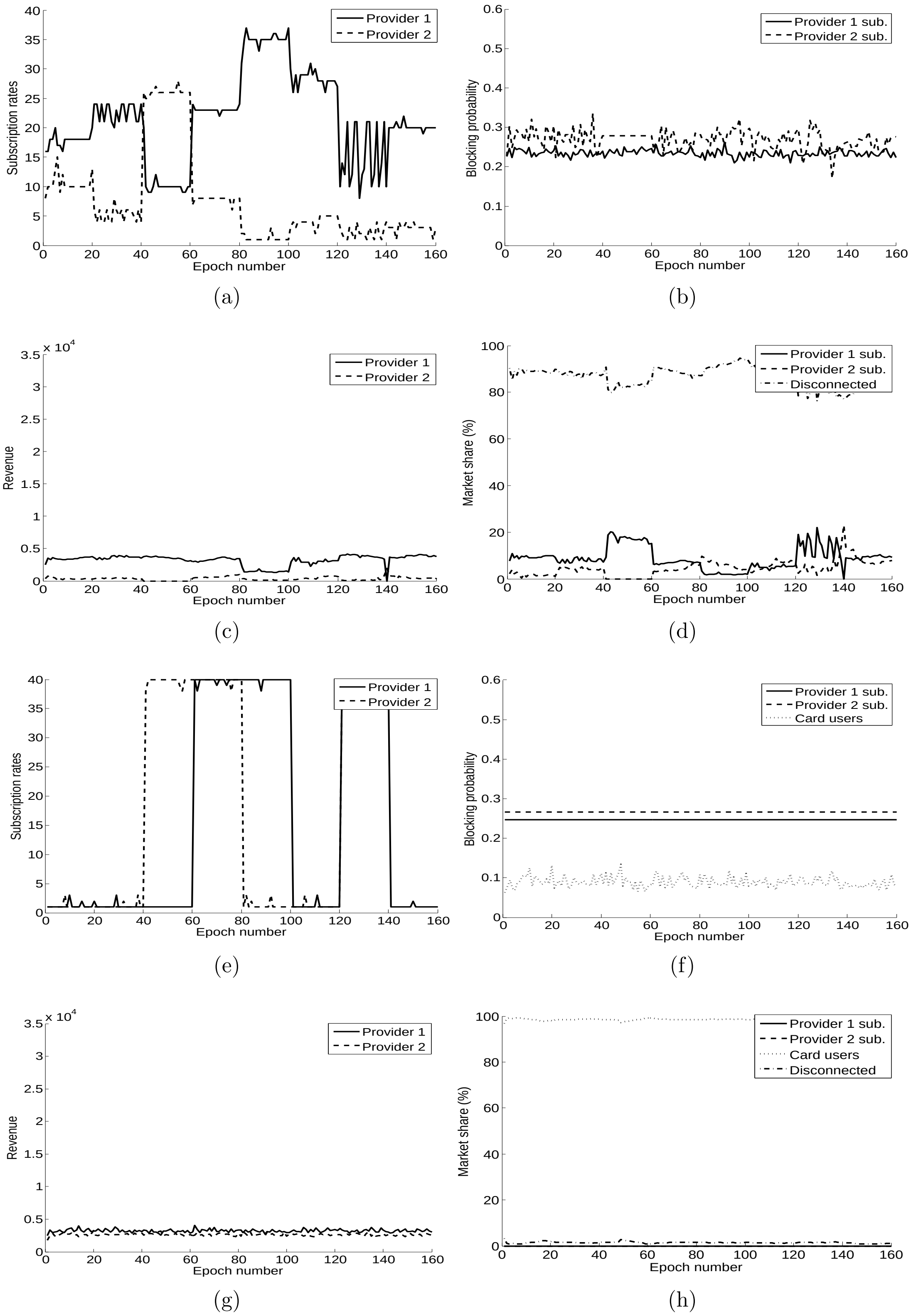
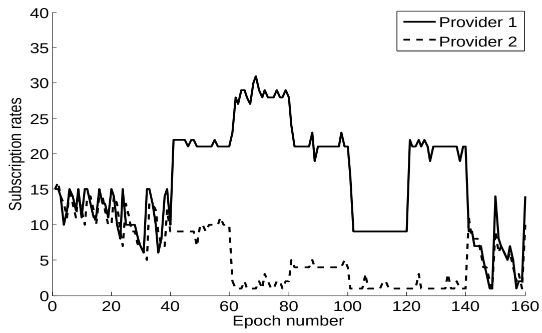
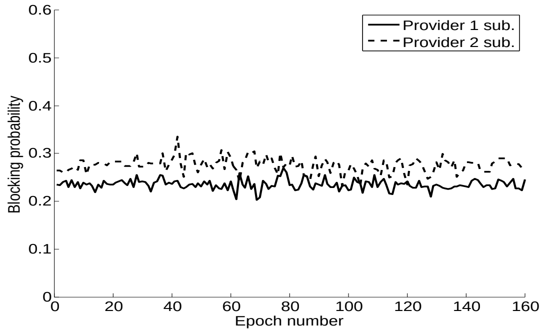


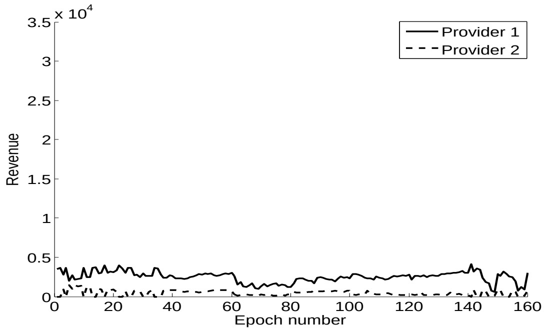
Figure B.16: BP scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market



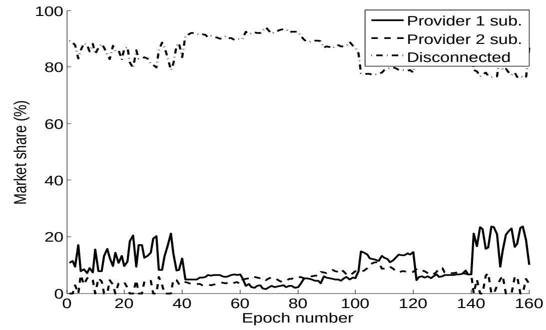
(a)



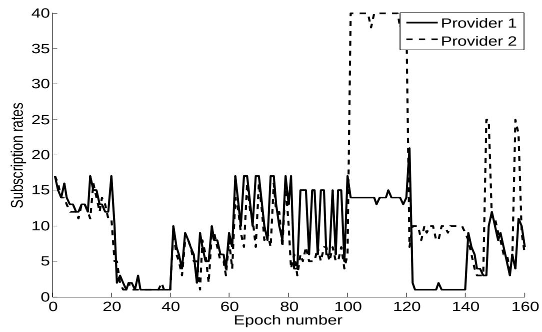
(b)



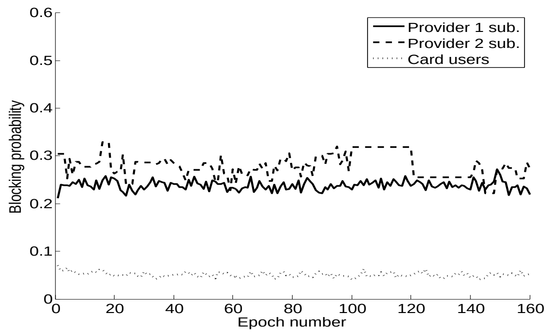
(c)



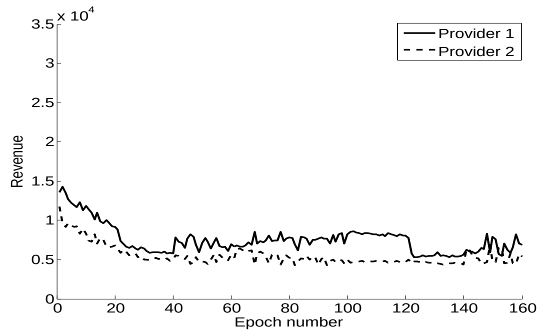
(d)



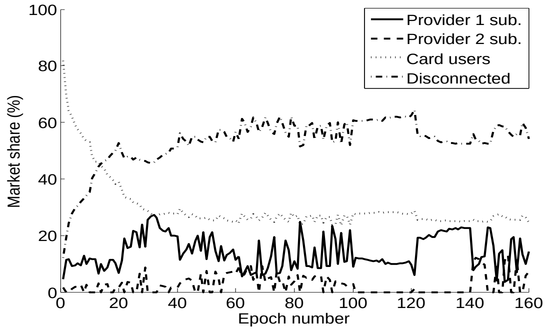
(e)



(f)



(g)



(h)

Figure B.17: PR scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

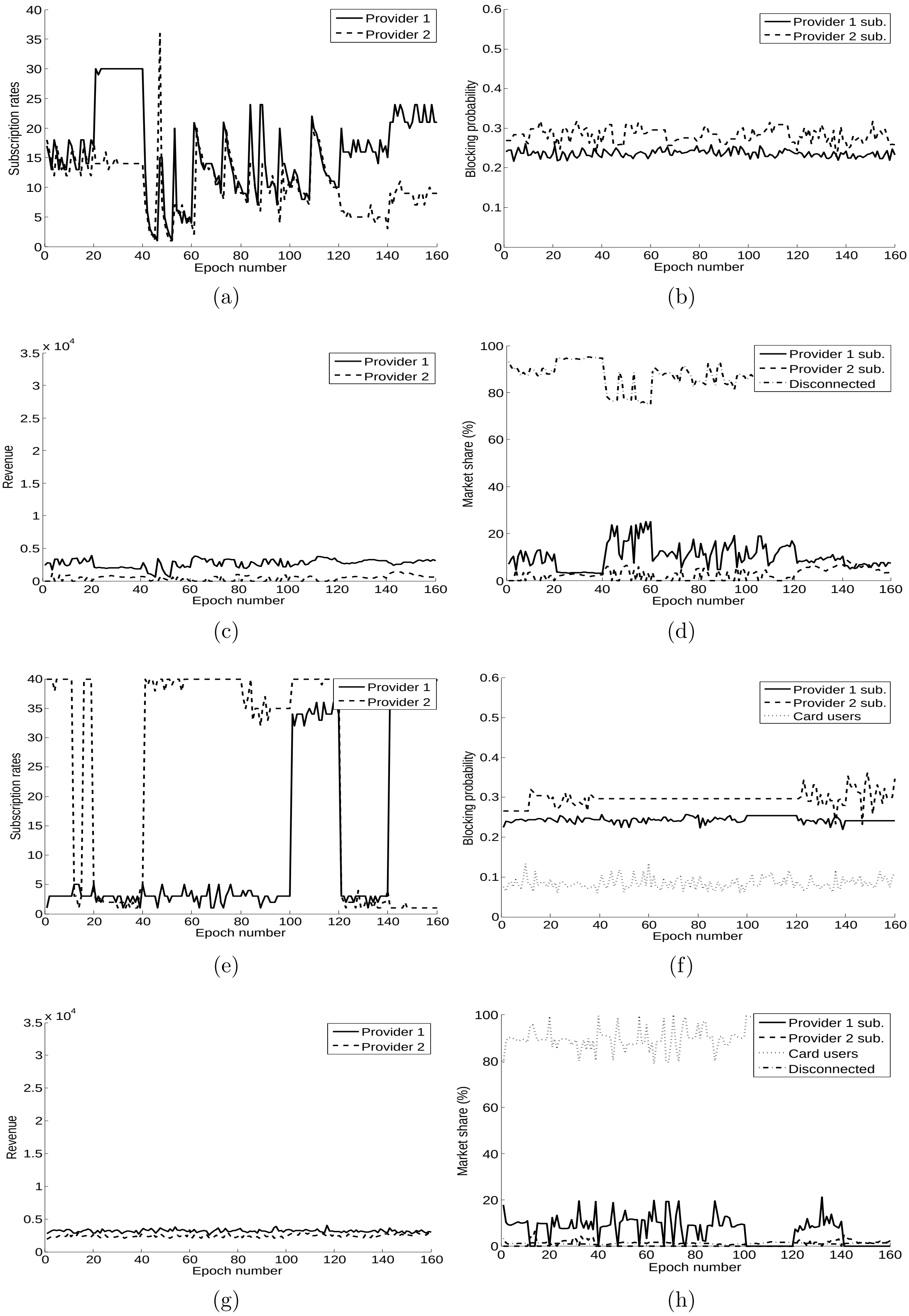


Figure B.18: PP scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

B.4 Low blocking probability threshold

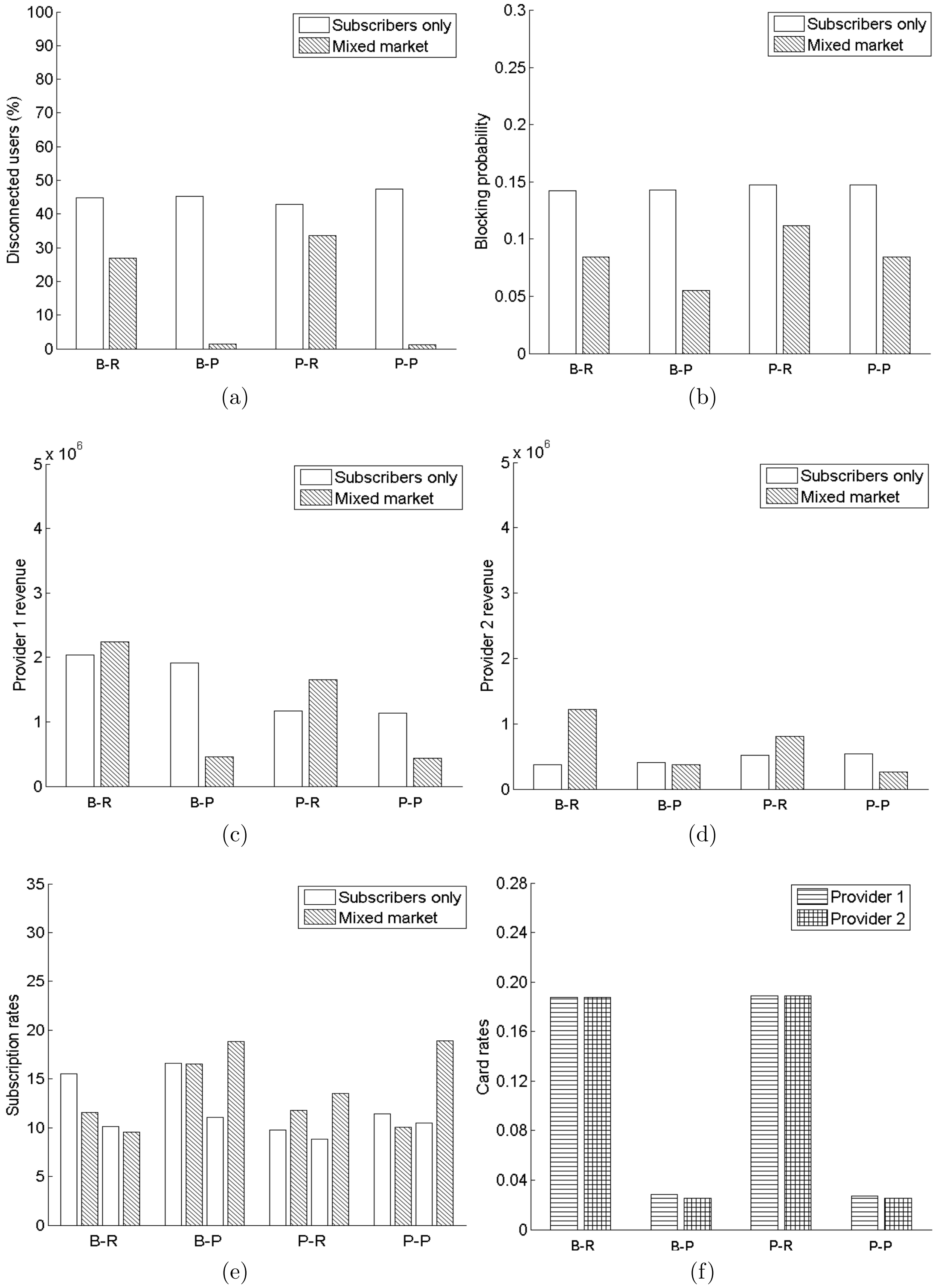


Figure B.19: (a) Percentage of disconnected users. (b) Blocking probability. (c), (d) revenue of providers. (e) Subscription rates. (f) Card rates.

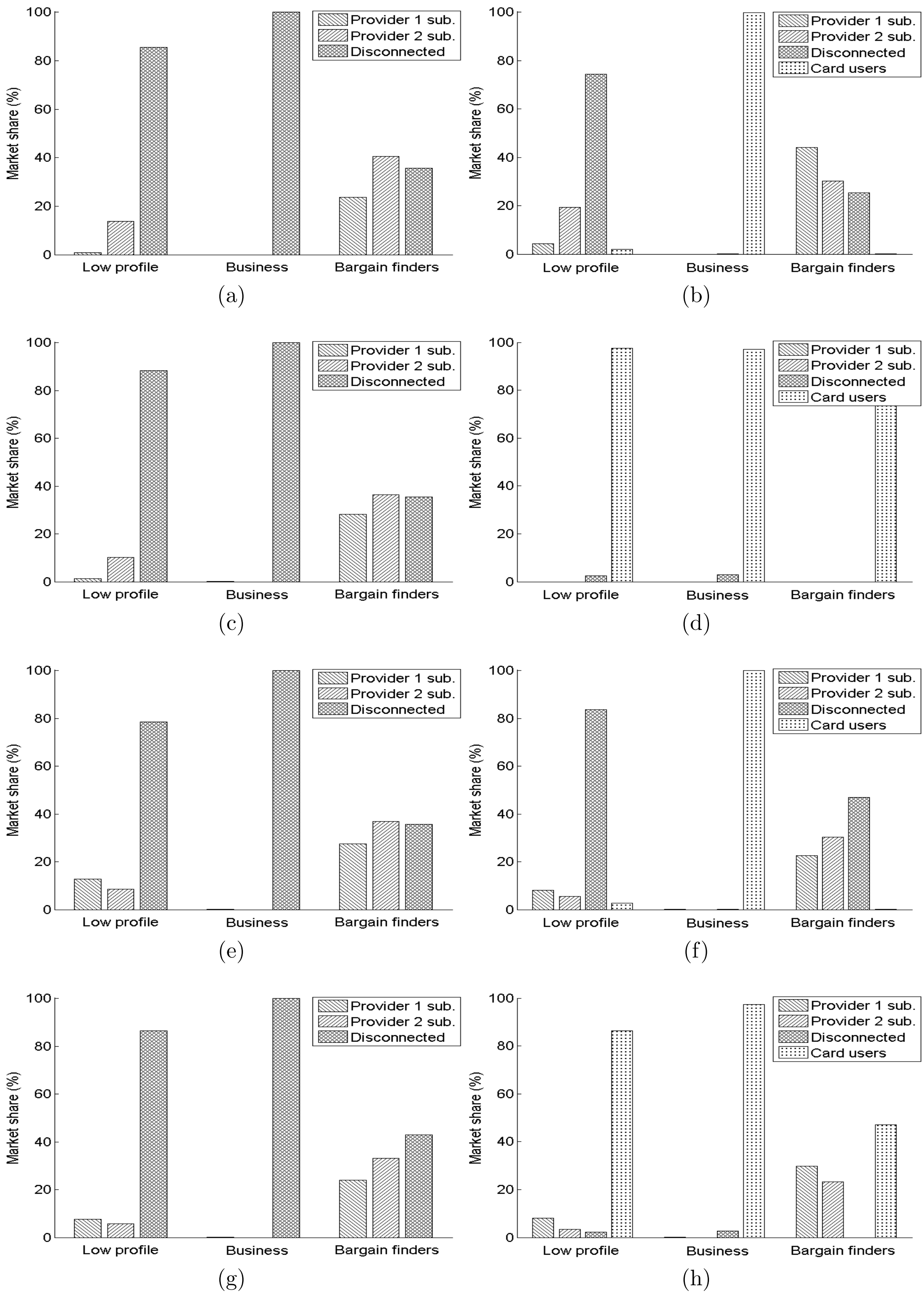


Figure B.20: **BR scenario**: only-subscriber market (a), mixed market (b). **BP scenario**: only-subscriber market (c), mixed market (d). **PR scenario**: only-subscriber market (e), mixed market (f). **PP scenario**: only-subscriber market (g), mixed market (h).

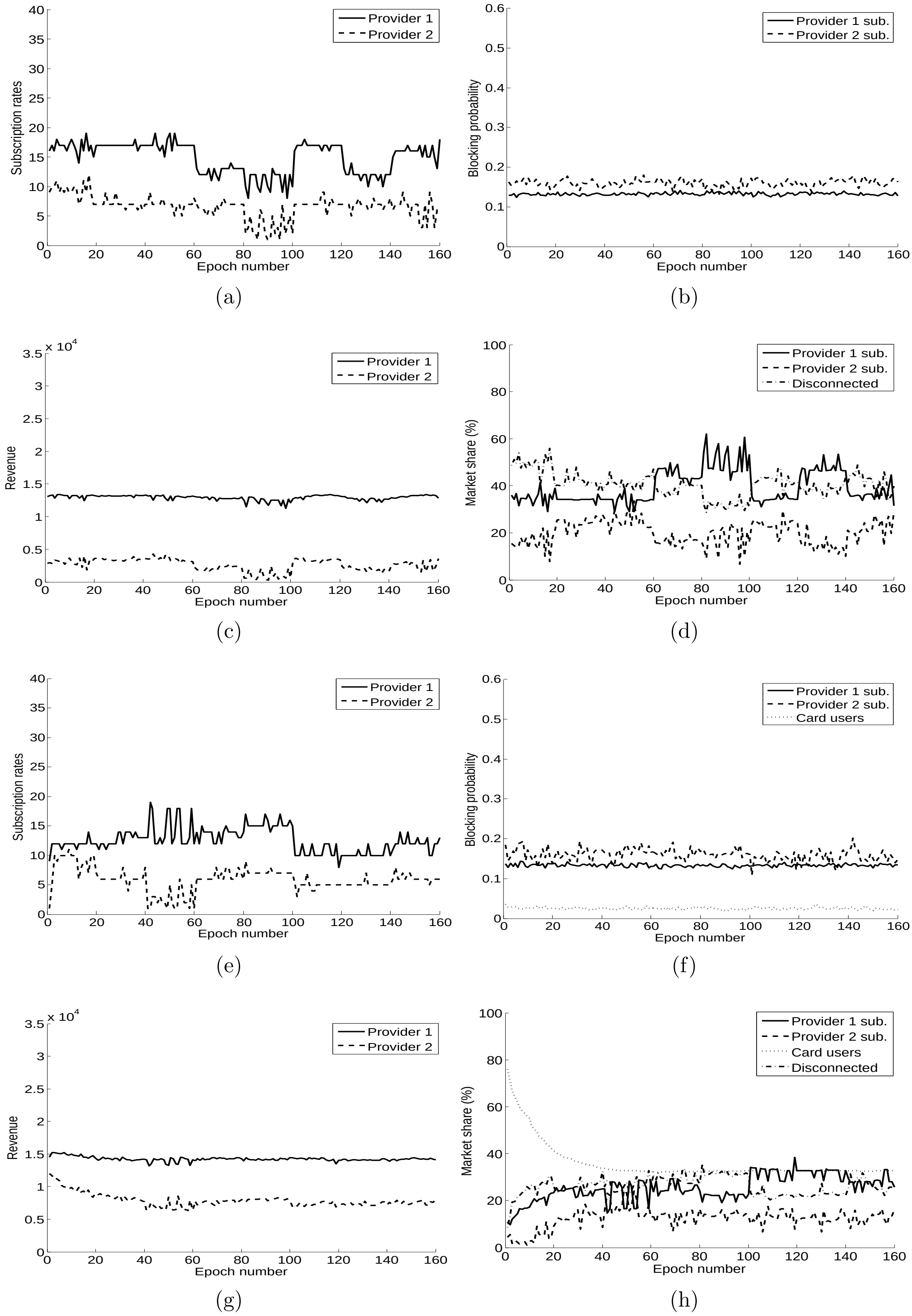


Figure B.21: BR scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

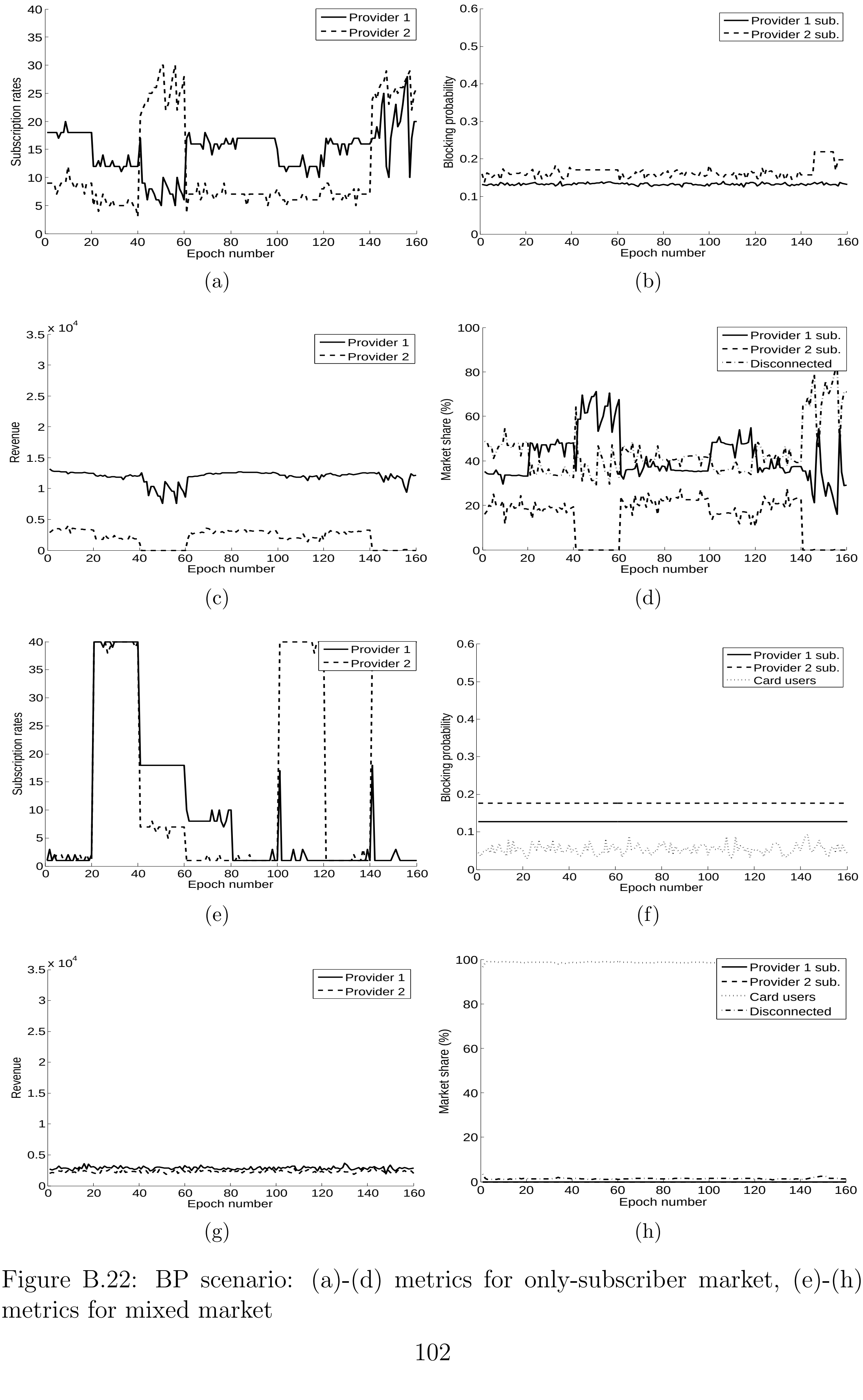


Figure B.22: BP scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

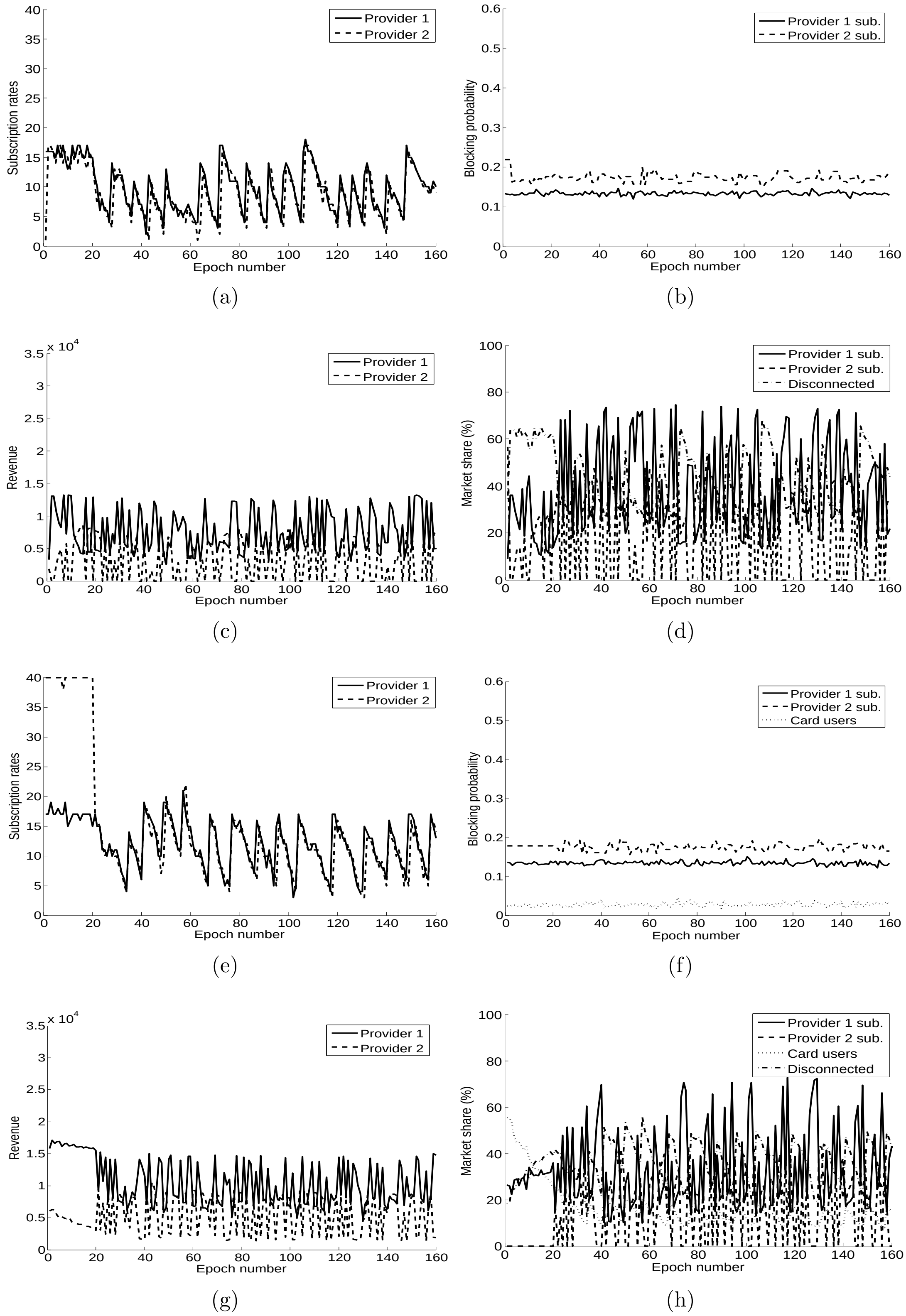


Figure B.23: PR scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

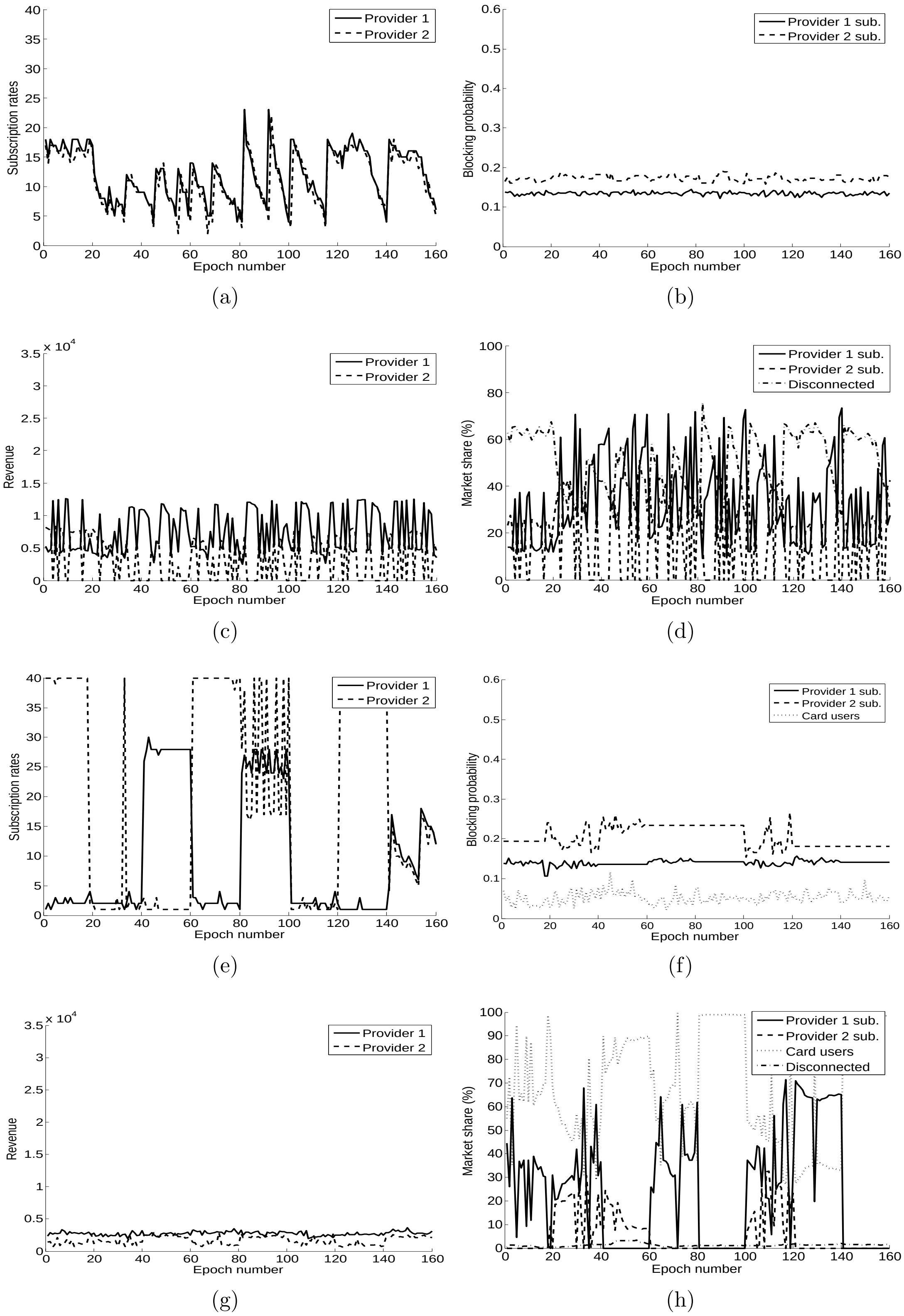


Figure B.24: PP scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

B.5 High demand

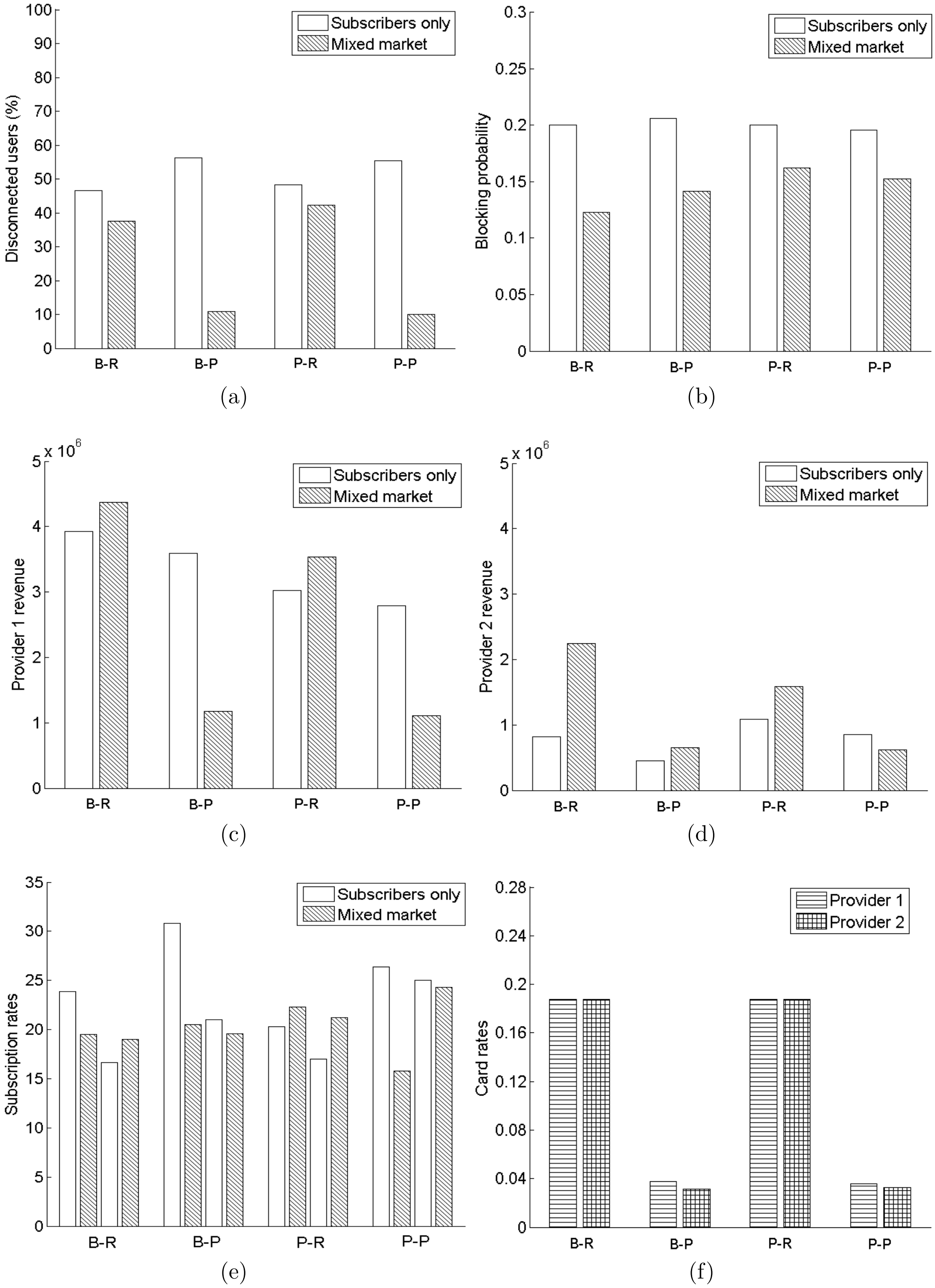


Figure B.25: (a) Percentage of disconnected users. (b) Blocking probability. (c), (d) revenue of providers. (e) Subscription rates. (f) Card rates.

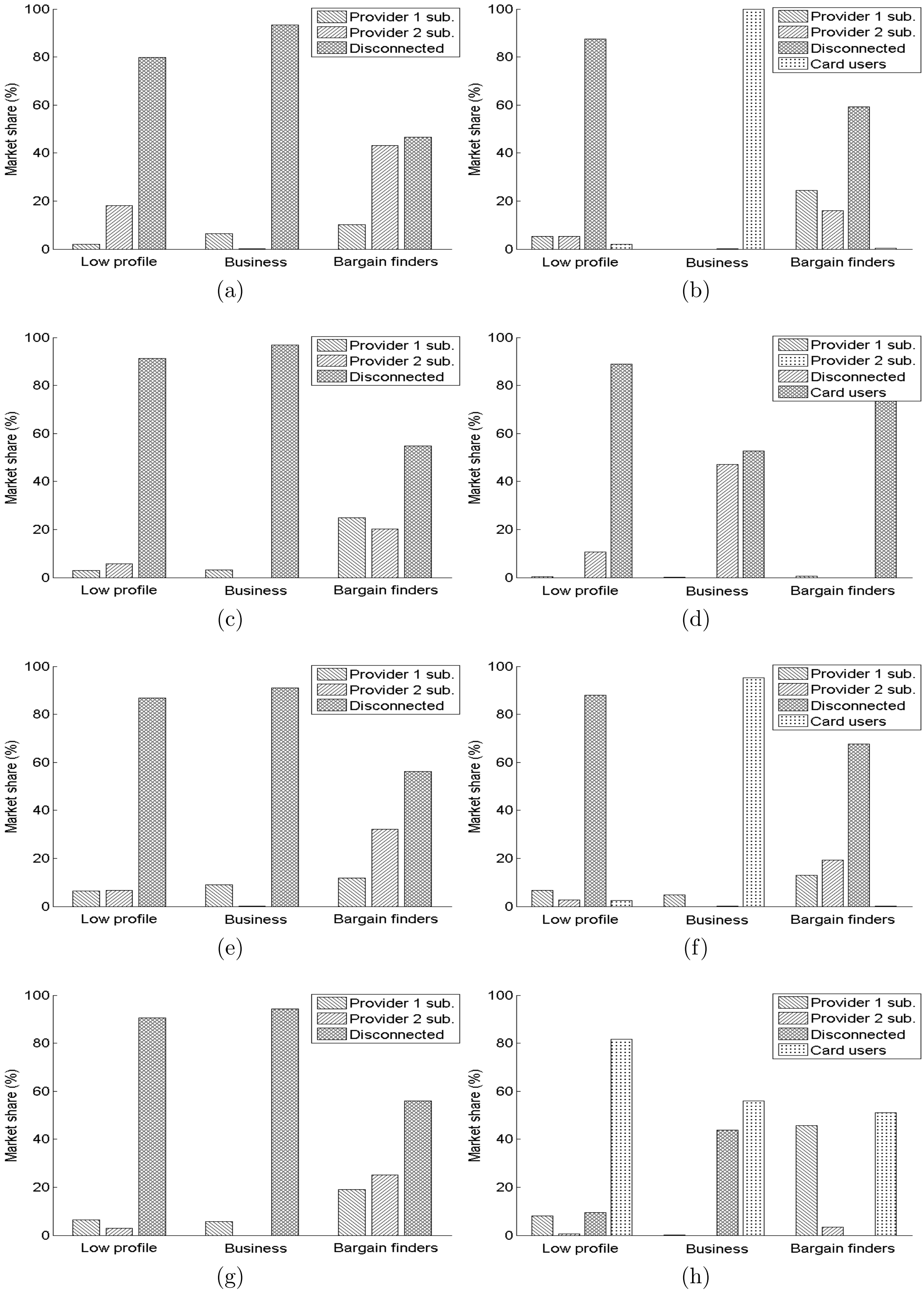


Figure B.26: **BR scenario**: only-subscriber market (a), mixed market (b). **BP scenario**: only-subscriber market (c), mixed market (d). **PR scenario**: only-subscriber market (e), mixed market (f). **PP scenario**: only-subscriber market (g), mixed market (h).

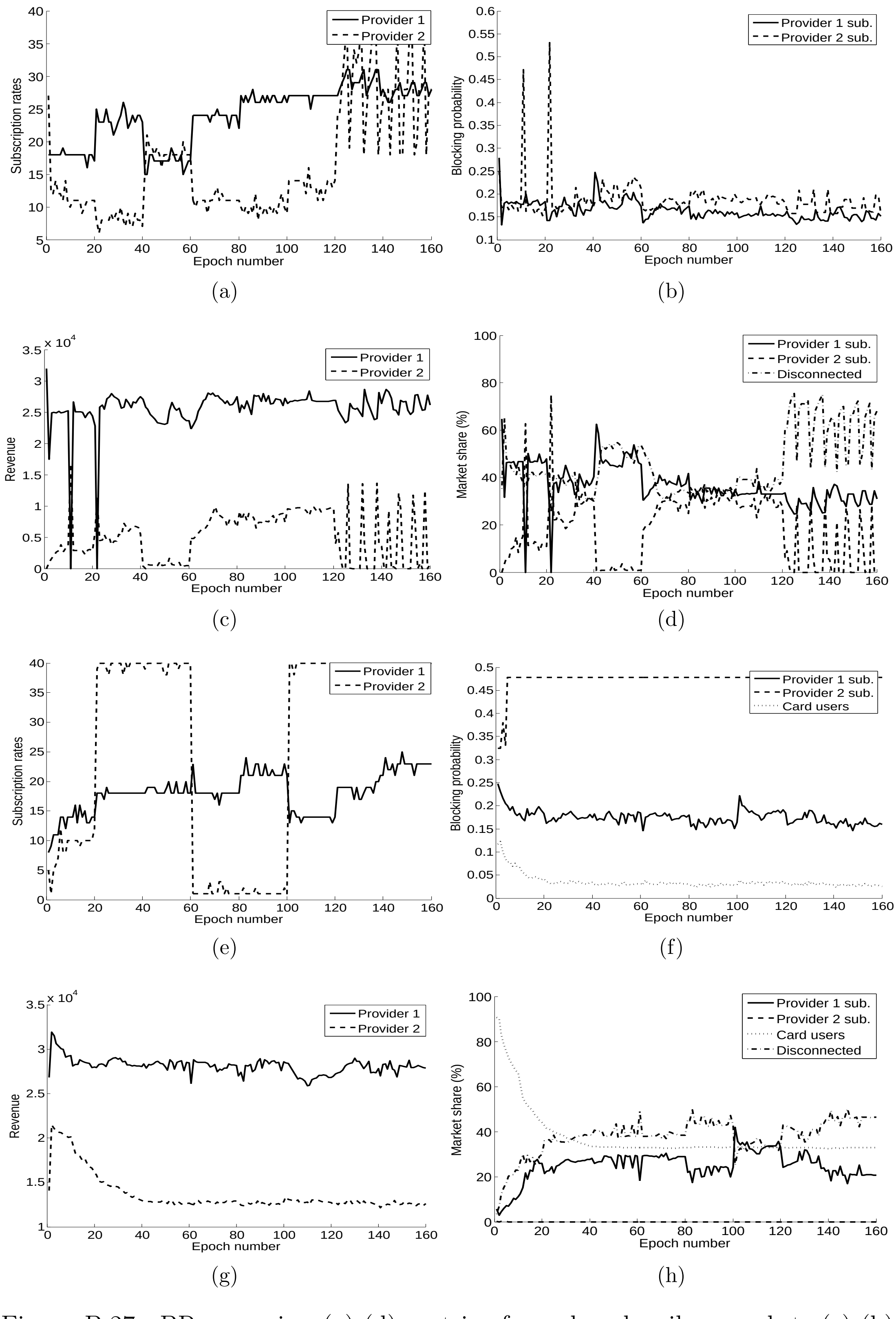


Figure B.27: BR scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

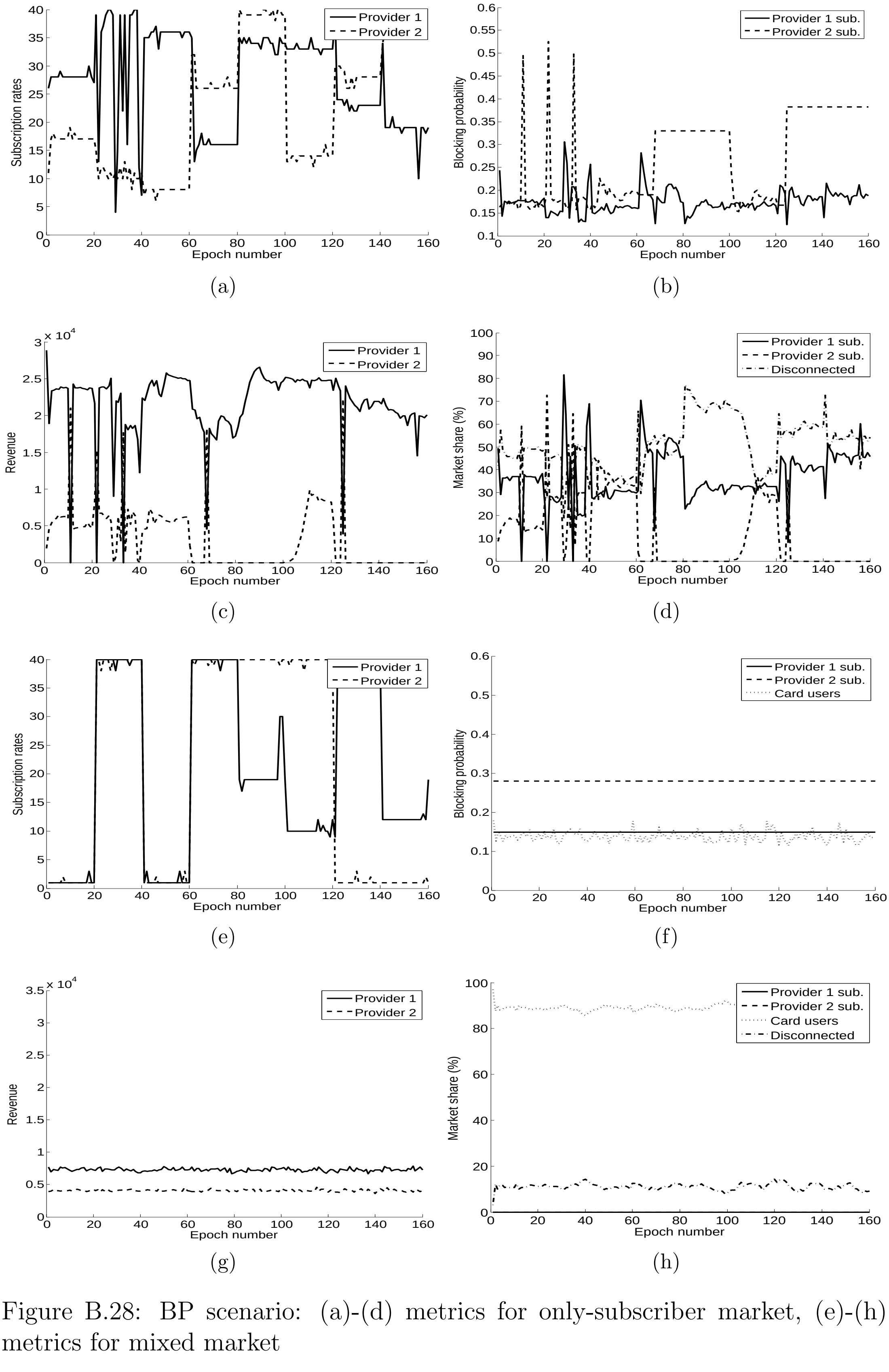


Figure B.28: BP scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

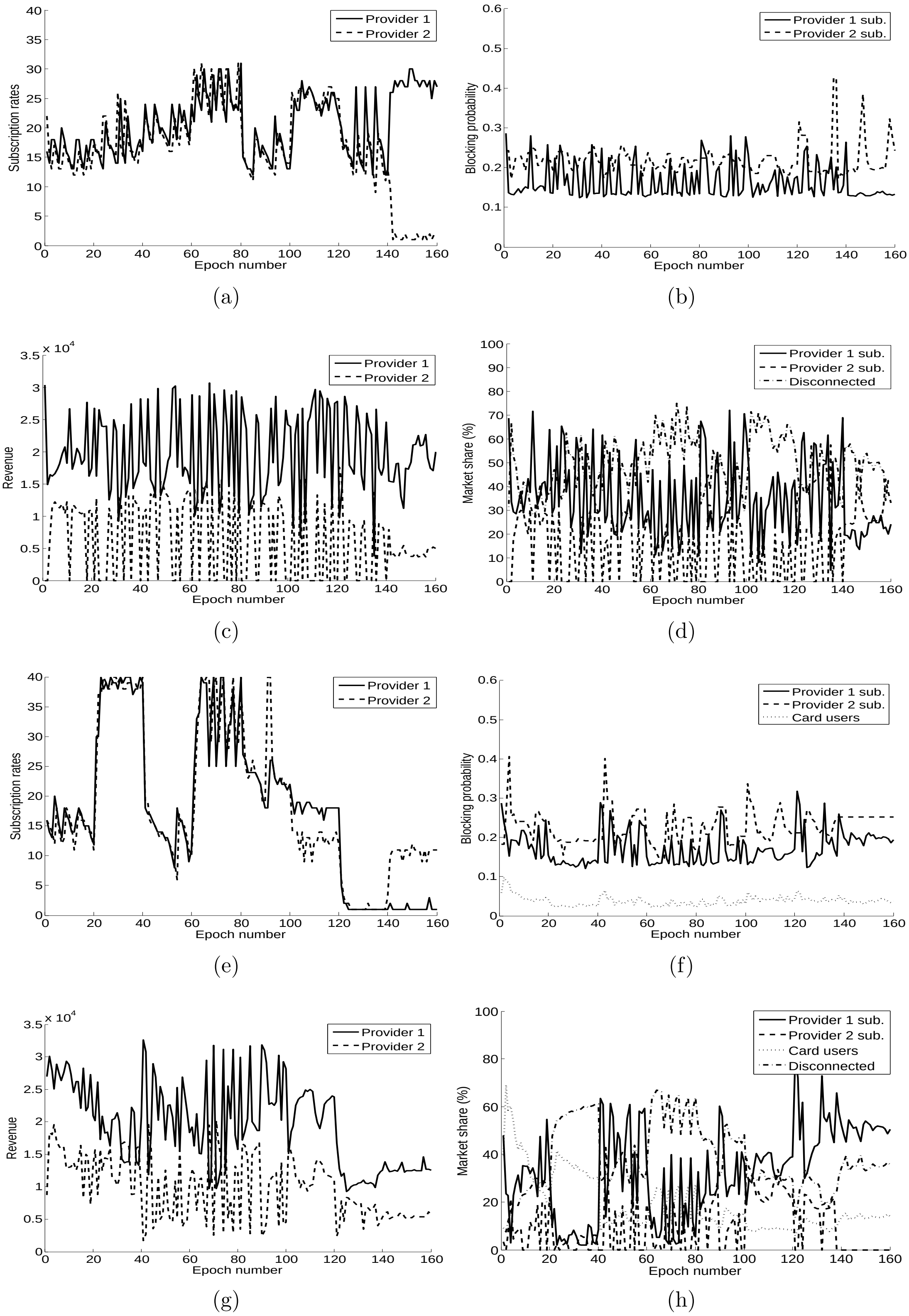


Figure B.29: PR scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

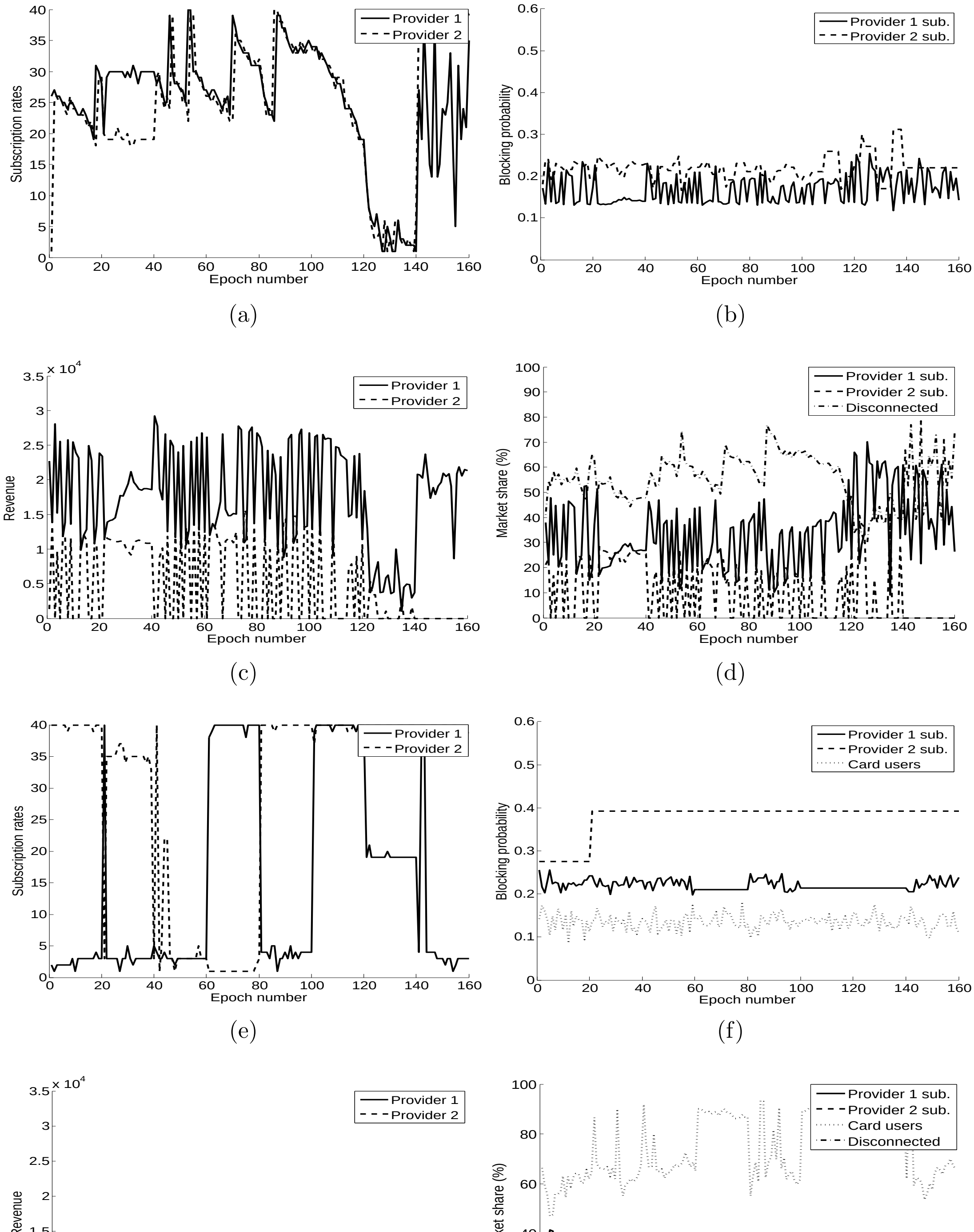


Figure B.30: PP scenario: (a)-(d) metrics for only-subscriber market, (e)-(h) metrics for mixed market

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