On the Impact of User Demand and Willingness-to-pay on Price Setting of MVNO and MNO Assuming Unlimited Network Capacity

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Thesis submitted in partial fulfillment of the requirements for the

Masters' of Science degree in Computer Science

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Abstract

Optimal spectrum utilization in conjunction with sophisticated pricing strategies have direct impact on the revenue of operators. Moreover, based upon the knowledge of wireless user characteristics, like traffic demand and willingness-to-pay, operators can design appropriate tariff plans that can increase their profit. On the other hand, users might have conflicting interests and preferences, e.g., with respect to price and Quality of Service (QoS).

A common business model of wireless network virtualization is the Mobile Virtual Network Operator (MVNO) paradigm. MVNOs are wireless service providers that do not own network components, but lease spectrum and network infrastructure from a Mobile Network Operator (MNO). In the first part of this thesis, we focus on the pricing of MVNOs in the retail market and the charging scheme of a hosting MNO in the wholesale market. We show that, in the absence of capacity constraints (i.e., unlimited network capacity), the optimal pricing strategies for both operators only depend on the distribution of users' willingness-to-pay. Our analysis demonstrates that when the MVNO or the MNO estimate inaccurately the users' willingness-to-pay and employ this estimation in price setting, the profit of both operators is affected. Furthermore, the "*cooperation*" in price setting between the MVNO and MNO can result in higher profit compared to the case where they *act independently*.

The second part of the thesis models a wireless market where users with specific traffic demand in voice, text, and data, select the optimal tariff plan, i.e., the plan that minimizes their cost. Taking into account the uncertainty in users' estimation of traffic demand, we analyze the tariff plan selection. As the uncertainty increases, users do not select the optimal tariff plan, and consequently, spend more. Moreover, the number of disconnected users increases, while some users may even spend more than their willingness-to-pay. Finally, operators seem to benefit, as their profit increases with users' uncertainty.

Περίληψη

Η βέλτιστη εκμετάλλευση του φάσματος σε συνδυασμό με τις εξελιγμένες τεχνικές τιμολόγησης έχουν άμεση επίδραση στα κέρδη των παρόχων. Επιπλέον, βασιζόμενοι στη γνώση των χαρακτηριστικών των ασύρματων χρηστών, όπως είναι η ζήτηση και το επιθυμητό ποσό που είναι διατεθειμένοι να πληρώσουν γι΄ αυτήν οι χρήστες, οι πάροχοι έχουν τη δυνατότητα να σχεδιάσουν κατάλληλα πακέτα ομιλίας με σκοπό να μεγιστοποιήσουν τα κέρδη τους. Από την άλλη πλευρά, οι χρήστες μπορεί να έχουν διαφορετικά ενδιαφέροντα και προτιμήσεις όσον αφορά την τιμή και την ποιότητα υπηρεσίας (QoS).

Ένα χαρακτηριστικό παράδειγμα εφαρμογής των εικονικών δικτύων στον τομέα των επιχειρήσεων είναι αυτό του εικονικού παρόχου ασύρματων υπηρεσιών (MVNO). Οι εικονικοί πάροχοι ασύρματων υπηρεσιών δεν διαθέτουν δικό τους δίκτυο, αλλά δανείζονται φάσμα και δικτυακή υποδομή από παρόχους ασύρματων υπηρεσιών (MNO). Στο πρώτο μέρος της παρούσας εργασίας επικεντρωνόμαστε στο μοντέλο τιμολόγησης ενός εικονικού παρόχου ασύρματων υπηρεσιών που δραστηριοποιείται στη λιανική αγορά και ενός παρόχου ασύρματων υπηρεσιών, ο οποίος παρέχει στον πρώτο πρόσβαση στο δίκτυό του και τον χρεώνει σε επίπεδο χονδρικής. Στην περίπτωση που δεν υπάρχουν περιορισμοί χωρητικότητας στο δίκτυο (δηλ., άπειρη χωρητικότητα δικτύου), αποδεικνύουμε ότι η βέλτιστη στρατηγική τιμολόγησης και για τους δύο παρόχους, εξαρτάται μόνο από την κατανομή που παρουσιάζει το επιθυμητό ποσό των χρηστών. Η ανάλυσή μας δείχνει ότι αν οποιοσδήποτε από τους παρόχους (MVNO ή MNO) εκτιμήσει λάθος τα χαρακτηριστικά του επιθυμητού ποσού των χρηστών και χρησιμοποιήσει αυτήν την εκτίμηση στην τιμολόγηση, επηρεάζεται το κέρδος και των δύο. Επιπλέον, η «*συνεργασία*» ανάμεσα στους δύο παρόχους στην τιμολόγηση μπορεί να συμβάλλει στην αποκόμιση μεγαλύτερου κέρδους, σε σχέση με την περίπτωση όπου *λειτουργούν ανεξάρτητα*.

Το δεύτερο μέρος της εργασίας μοντελοποιεί μια ασύρματη αγορά στην οποία χρήστες με συγκεκριμένη ζήτηση σε χρόνο ομιλίας, μηνύματα κειμένου, και δεδομένα, διαλέγουν το βέλτιστο πακέτο ομιλίας, δηλαδή αυτό με το ελάχιστο κόστος. Λαμβάνοντας υπ΄ όψιν την αβεβαιότητα στην εκτίμηση των χρηστών για τη ζήτησή τους, εξετάζουμε πως διαφοροποιούνται οι επιλογές τους. Καθώς η αβεβαιότητα αυξάνεται, οι χρήστες δεν επιλέγουν το βέλτιστο πακέτο ομιλίας, συνεπώς τα έξοδά τους είναι αυξημένα. Επιπλέον, ο αριθμός των χρηστών που μένουν εκτός αγοράς αυξάνεται, ενώ είναι πιθανόν κάποιοι χρήστες να ξοδέψουν περισσότερα απ΄ όσα ήταν διατεθειμένοι να δώσουν. Τέλος, οι πάροχοι φαίνεται να επωφελούνται καθώς τα κέρδη τους αυξάνονται με την αβεβαιότητα των χρηστών.

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To my family

Στην οικογένειά μου

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Chapter 1

Introduction

Wireless access, use and traffic demand are on a fast rise, leading to an increased request for radio spectrum. According to forecasts, by 2018, the mobile data traffic will exceed the 131.6 exabytes per month worldwide [2]. Besides performance reasons, the efficient spectrum utilization is imperative from an economic point of view: spectrum is a scarce resource of high economic value for both the society and the wireless industry with a wide variety of active business stakeholders [3]. To increase spectral efficiency, the research community has been developing Multiple Input Multiple Output systems (MIMO), intelligent and directional antennas, as well as improved channel assignment, topology control, and MAC protocols. Same direction also follow Cognitive Radio Networks (CRNs) and network virtualization. Cognitive radios aim 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 [4]. Similarly, network virtualization has the potential to improve spectrum utilization, by allowing external entities to participate in the market, or leasing infrastructure and under-utilized spectrum from a network operator.

In computing, network virtualization is the process of combining hardware and software network resources and functionality into a single, software-based administrative entity, a virtual network. Network virtualization involves platform virtualization [5], often combined with resource virtualization. Wireless network virtualization can have a very broad scope ranging from spectrum sharing, infrastructure virtualization, to air interface virtualization. Similar to wired network virtualization, in which physical infrastructure owned by one or more providers can be shared among multiple service providers, wireless network virtualization needs the physical wireless infrastructure and radio resources to be abstracted and isolated to a number of virtual resources, which then can be offered to different service providers.

From operators' perspective, optimal spectrum utilization and pricing strategies are of high importance, as they have direct impact on network performance and profitability. Operators should minimize spectrum white spaces and ensure that users receive the highest achievable Quality of Service (QoS), based on the available bandwidth and transmission technology. Consequently, spectrum pricing should be performed carefully to retain subscribers to their network and optimize profit. A high price would prevent users from buying their services and possibly subscribe to a competitor, while a low price could increase data traffic, contributing to congestion and QoS degradation.

On the contrary, users have conflicting interests and preferences, e.g., with respect to price and QoS. Today, users demand ubiquitous connectivity anywhere and anytime. New affordable smartphones with increased capabilities have introduced in the market. The number of connected devices has been growing dramatically [2]. The deployment of new technologies enable more players to participate in the market, improve network services, and accelerate the evolution of wireless networks. It is straightforward that low price and high QoS are admittedly users' main objectives when selecting a wireless provider. The expansion of wireless markets, combined with operators' competition and advanced user equipment, allow users to achieve higher payoffs, thus contributing to their welfare.

1.1 Motivation

Besides technical interest, user characteristics, namely traffic demand and willingness-to-pay (WtPay), play a key role in pricing structures and tariff plan design. Mobile Virtual Network Operator (MVNO) is a common paradigm of network virtualization. MVNOs are wireless service providers that do not own network infrastructure but lease spectrum or network components from a Mobile Network Operator (MNO), and resale access services in the retail market. The economic interaction among MNOs, MVNOs, and users has been widely modeled in the literature. Some studies try to identify the impact of content investment, while others are interested in competition amongst heterogeneous customers with different brand appeal perception and price preferences [6, 7]. There are studies considering cognitive virtual network operators, and examine their functionality and profitability [8–12]. A cognitive operator can obtain spectrum resource via both spectrum sensing, as in the hierarchical-access approach and dynamic spectrum leasing, as in the dynamic exclusive use. There are also approaches, considering scenarios where a virtual operator deploys improved technology deployment compared to its competitors, which allows a more efficient use of the spectrum [13]. However, to the best of our knowledge, there is no study considering user feedback on pricing. Questions that naturally arise are related to the impact of user profile on price setting and revenue of operators. Can the cooperation among providers allow them to increase further their market share? These questions motivate this work.

The second part of this thesis takes into consideration the user/consumer perspective. There is a rapid growth in the generated mobile demand, however, the majority of users have a crude estimation of their traffic demand. Mobile operators tend to offer their customers a choice among a variety of tariff plans. Subscribers attempt to select the tariff plan, which best suits their needs according their traffic patterns. However, is the selected tariff plan really the best choice based on their actual traffic demand? How does the accuracy of the traffic demand estimation affect the user selection? Does perfect knowledge of the user demand contribute to the optimal selection, and consequently, to money savings? These questions are the driving force of the thesis.

In addition, national regulatory authorities (e.g., BEREC in Europe, FCC in USA, and Ofcom in UK) regulate communications and promote competition, innovation and investment in broadband services and facilities. They encouraging the highest and best use of spectrum domestically and internationally, while, on users' side, they inform the consumers of their rights and obligations, and safeguard their rights on telecommunication services. Recently, FCC announced that one in six mobile users have experienced "bill shock", a sudden and unexpected increase in monthly bills that is not caused by a change in tariff plans [14]. This fact indicates that wireless users are confused by mobile phone charging. These phenomena motivate us to investigate pricing structures.

1.2 Objectives

The first objective is to develop novel pricing strategies for an MNO and an MVNO by exploiting the knowledge about the user profile (i.e., traffic demand and WtPay preferences). The second objective is the assessment of the impact of a "cooperative" interaction between the MVNO and MNO on the price setting. The u-map [1,15–17] is a crowdsourcing platform that empowers users with recommendations about network providers and collects information about these user characteristics. Moreover, we are particularly interested in examining how the u-map can contribute towards this direction, by providing information about user preferences.

The third objective is the evaluation of the impact of the inaccuracy in traffic demand estimation on tariff plan selection. Our aim is the development of a modular and simulation platform that instantiates users with specific characteristics in their traffic demand and WtPay. The platform incorporates a finite number of tariff plans, as they are offered by operators in wireless markets, and models the user profile and tariff plan selection process.

1.3 Challenges

Obtaining knowledge about the user preferences is non-trivial task since users are characterized by high heterogeneity in their usage behavior and traffic demand [18, 19]. These patterns may change also dynamically making it even harder for operators to obtain and exploit the knowledge about them. Similarly, the WtPay is private information that cannot be easily inferred.

However, it is unclear how users' traffic demand and WtPay can be modeled realistically. In the literature, there are several studies analyzing the wireless traffic characteristics [18–23], but as far as we know, there are not widely accepted models for specific types of services. Moreover, the user diversity with respect to the traffic demand and services imposes additional challenges in the modeling process.

Nowadays the tariff plans can be complex: They offer numerous options, add-ons, and volume related discounts. Some tariff plans treat all network calls as being equivalent, whilst others use price differentiation between subscribers of different network operators, or even between subscribers of the same network, but users of different tariff plan (e.g., Cosmote What's Up, Vodafone CU). There are plans offering unlimited data, but degrade QoS when consumption exceeds a specific threshold, and others that offer special services, such as sport or music (e.g., Spotify) streaming services. Most tariff plans are monthly-based, while others are pay-per-use. Network operators do not always state how discounts work for landline calls, and calls or sms to special services, like information or news services. This list is not exhaustive, but it should be sufficient to indicate the complexity of tariff plan structures in wireless access markets. Moreover, the user selection process is characterized by various psychological (e.g., brand name and perceived reliability of a provider), technological (e.g., QoS and QoE in the context of various services offered by a provider), and economical (e.g., WtPay) aspects, which are hard to be modeled precisely.

1.4 Contributions

This master thesis makes the following contributions:

1. It provides theoretical and simulation analysis of the economic interaction between an MVNO and its host MNO under the assumption of unlimited network capacity. It focuses on the joint problem of price setting between operators and evaluates the contribution of the u-map towards this direction. We show that in the absence of capacity constraints, if both operators aim at maximizing their wealth share, their pricing policies at the wholesale and the retail market only depend on the distribution of users' WtPay.

2. It presents a modeling framework and simulation platform that allows us to instantiate an heterogeneous population of users and their economic interaction with a finite number of tariff plans. It incorporates models for users' wireless traffic demand—in terms of voice minutes, text messages (sms), and data— tariff plans, charging functions, and WtPay preferences. The simulation environment of this framework is modular, in that it can instantiate and implement different models for the aforementioned parameters.

3. It analyzes the impact of the uncertainty in traffic demand estimation, on the revenue of operators and on user spendings. We show that the precise knowledge of traffic demand provides significant benefits to the subscribers, namely the selection of the tariff plan that minimizes their cost. On the contrary, it is shown that operators could benefit from users' inaccuracy and bias.

1.5 Roadmap

The remainder of this thesis is organized as follows: In Chapter 2, we discuss the related work in the area of cellular network economics. First, we provide a brief description of network virtualization and describe the concept of MVNO. Then, we present a detailed analysis of studies considering interaction between virtual operators and users in spectrum markets. Finally, there is a discussion on charging strategies, consumer usage patterns, and user behavior under tariff plan selection in wireless networks, with a comparison of the respective literature.

Chapter 3 presents the background work, namely the u-map system and the CoRLAB. We overview the u-map architecture and main functionalities. We briefly discuss the CoRLAB, a multi-layer modeling framework and simulation platform for the analysis of large-scale markets, which is integrated with the u-map. The modeling framework and simulation platform of this M.Sc. thesis can be considered as part of the CoRLAB.

In Chapter 4, we study a wireless access market, where an MVNO serves a number of end users in the retail market, and an MNO provides access to the MVNO in the wholesale market. We provide a detailed analysis of the optimal pricing strategies that maximize operators' wealth share, in the absence of capacity constraints. The contribution of the u-map, in collecting information about user preferences is highlighted, and we demonstrate the consequences of partial information on operators' revenue.

In Chapter 5, we present our modeling framework and evaluate the impact of uncertainty in traffic demand on tariff plan selection. Specifically, we define the characteristics of an heterogeneous population, with specific traffic demand and WtPay preferences, and model a wireless market from an economic point of view. We incorporate a representative set of tariff plans, selected from the proposed by Greek wireless providers, and evaluate how users' inaccuracy in traffic demand estimation affects their choices and expenses. We provide some interesting insights and prove through simulations that users always benefit from the actual knowledge of their traffic demand. Finally, Chapter 6 concludes this thesis and discusses future work plans.

1.6 Related Publications

The economic interaction between an MNO and an MVNO in a wireless access market, described in Chapter 4, is the main contribution of the following publication:

1. "**Pricing for Mobile Virtual Network Operators: The contribution of u-map**", published in *IEEE DySPAN 2014* (short paper) by Charalampos Meidanis, Ioannis Stiakogiannakis, and Maria Papadopouli.

Chapter 2

Related Work

2.1 Network Virtualization

A recent trend in mobile communication industry is infrastructure sharing [24]. MNOs, in order to cope with the increased costs, required to maintain and roll out their network (3G, LTE) infrastructure, tend to explore various partnerships and resource sharing schemes. Infrastructure sharing can be realized in different ways, with most common of them being Passive Sharing and Active Sharing. Passive infrastructure sharing is the sharing of non-electronic equipment at cell site, which is most commonly used among operators, since there is no regulatory and legislation intervention, and it is easier to contract its setup and maintenance. In Active sharing, operators share electronic infrastructure (switches, antennas) as well as spectrum (spectrum trading), where an operator can lease part of its spectrum to another operator or service provider for commercial use.

2.1.1 Mobile Virtual Network Operators

In addition to infrastructure sharing, wireless network virtualization [25] is gaining attention, as it has the potential to improve spectrum utilization and facilitate different types of cooperation among operators and service providers. A common business model of wireless network virtualization is MVNO. MVNOs are wireless service providers that do not own network components, but lease spectrum and network infrastructure in some cases from an MNO. Then, they resale access services in the retail market just like an independent operator with its own network infrastructure. They supply the Subscriber Identity Module (SIM) card, handle their own billing, and have full control over their subscribers.

There are four main MVNO business models that emerge: Branded Reseller, Light-MVNO, Full-MVNO and Network enablers [26].

- **Branded reseller:** is the lightest MVNO business model, where the MVNO just provides its brand and, sometime, its distribution channels, while the MNO provides the rest of the business, from access network to the definition of the mobile service offer. This is the model that requires the lowest investment for a new venture, therefore the fastest to implement. However, most of the business levers remain with the network provider. Therefore, the new venture has a very limited control of the business levers and value proposition of the service.

- **Full-MVNO:** is the most complete model for a new venture, where the MNO just provides the access network infrastructure and, sometimes, part of the core network, while the MVNO provides the value added services (e.g., voice service, sms, etc.), the back office services (e.g., subscriber registration, handset, billing, and customer care) and the distribution channels. This MVNO business model is typically adopted by telecommunication players that could gain synergies from their current business operation.

- **Light-MVNO:** is an intermediate model between a branded reseller and a full-MVNO. This model allows new MVNOs to take control of the marketing and sales areas and, in some cases, increase the level of control over the back-office processes and value-added services.

- **Network enablers:** also known as Mobile Virtual Network Enablers (MVNE), this is a third party provider focused on the provision of infrastructure that facilitates the launch of MVNO operations. An MVNE can be positioned between a host MNO and an MVNO venture to provide services ranging from value added services and back office processes. MVNEs reduce the entry barriers of MVNO ventures, given that an MVNE aggregates the demand of small players to negotiate better terms and conditions with host MNOs.

Both in Europe and USA, MVNOs offer low cost offers compared to those of MNOs. In Europe, MVNOs tend to target specific user populations, such as low-WtPay users (e.g., with low charge-per-month offers), youngsters (e.g., with unlimited sms, voice minutes over the same network), and immigrants (e.g., special offers for calls to specific destinations). UK, in 1999 was the first European market to encounter MVNOs with the entry of Virgin Mobile. The UK market for mobile services is one of the largest (in terms of subscribers) in Europe. There are four major MNOs and two large MVNOs serving UK mobile subscribers. MVNOs Virgin Mobile UK and Tesco Mobil hold 5.91 % and 1.83 % market share, respectively [27]. Today, there are more than 40 MVNOs active in the UK mobile market [28].

The USA was one of the first countries to experience the emergence of MVNOs. In USA, MVNOs follow a different approach compared to Europe, as they do not target specific user populations, but offer a variety of tariff plans to attract customers of all user categories. MVNOs in the USA lease spectrum from major carriers such as AT&T Mobility, Sprint Corporation, T-Mobile US, and Verizon Wireless and resale their services. There are more than 80 active MVNOs in the USA offering voice and data services (e.g., Boost Mobile, BYO Wireless) and more than 15 MVNOs offering voice services (e.g., H2O Wireless, Jaguar Mobile). MVNOs that offer voice services usually provide additional services, such as sms and low-speed data access [29]. The concept of the MVNO and its penetration in telecommunication business is analyzed in details in [26, 27, 30, 31].

2.1.2 Competition among Providers

Competition between providers and users has been modeled widely in the literature. Several approaches try to shed light on the interaction of an MVNO with the spectrum owner and the end users, providing interesting insights about MVNOs profitability. This section briefly describes their main findings and methodology. Studies [8–12] consider a Cognitive Mobile Virtual Network Operator (C-MVNO), which can both sense and lease spectrum from a spectrum owner to obtain the available bandwidth. In [9, 10], Li *et al.* examine a wireless market with dynamic network characteristics, such as dynamic user demand and uncertainty in spectrum sensing, and study the profit maximization problem under different pricing strategies. They provide both theoretical and simulation analysis, and propose algorithms that perform revenue maximization, by applying pricing and market control, and cost minimization, by employing proper resource investment and allocation. Spectrum price is considered dynamic, as it may vary over time. User requests are modeled with queuing dynamics, while the C-MVNO might accept or reject a new request based on the available slots. Users have WtPay pay preferences, modeled as i.i.d random variable unknown to the operator and their demand is modeled as random file sizes, drown from a discrete distribution, which are independent of price. Time varying price affects user incentives of downloading requests. The authors' aim is to develop a low-complexity online control policy that determine pricing and resource scheduling without knowing the statistics of dynamic network parameters.

In [8, 12], Duan *et al.* study the optimal spectrum investment (by both spectrum sensing and spectrum leasing) and pricing decisions of a C-MVNO by providing mathematical and simulation analysis. They assume that users are equipped with software define radios and can tune to transmit in a wide range of frequencies, while spectrum sensing is performed only from the C-MVNO and not from the users. User achievable rate is defined by Shannon Law and depends on the allocated bandwidth from the operator, user transmission power and channel gain, and the noise power per unit bandwidth. User payoff is assumed to be a function of the allocated bandwidth and price, i.e., the difference between the data rate and the linear payment. User demand considered as a function of the user wireless characteristics and the price. Is assumed that a user with a better channel condition or a larger transmission power has a larger demand. They model the interaction between the C-MVNO, and end-users using game theory (Stackelberg game), and conclude that spectrum sensing can both benefit users' payoffs and operators' expected profit. Duan *et al.* [11] also model the interaction of two C-MVNO in a retail market with the characteristics described above and compare the competition of the two C-MVNOs with the coordinated case, where the two operators cooperate to maximize their profit. They show that the maximum loss of total profit due to operators' competition is no larger than 25%. In a similar way, Duan *et al.* [32] consider a market of the same wireless and user characteristics and provide a detailed mathematical analysis of the strategic interactions of two competing MVNOs who need to make the optimal spectrum investment (leasing) and pricing decisions. Both operators lease spectrum from a spectrum owner on a short-time scale. They conclude that competition leads to more aggressive leasing and lower prices of the operators, and thus, higher payoffs for the users. However, none of the above studies takes into consideration MNO's profit and pricing model, as well as the interaction between the spectrum owner and the end users.

Unlike previous studies, there are approaches where the spectrum owner (MNO) is active in the market and competes with the MVNO. In [7], Debbah *et al.* consider the competition between an MNO and an MVNO on a population of heterogeneous customers (i.e., in terms of brand appeal and added value perception) and provide a mathematical study of operators' interaction and customers' responses. Is assumed that MVNO buys resources from the MNO at the wholesale price and offers an added value, supposed to be better than MNO's, and lower price than MNO. Each user is characterized by his perception of brand appeal and his perception of added value, while MNO is assumed that offers a higher brand appeal perception. Market population is segmented into two groups: the first one refers to the users that are more sensitive to brand appeal and thus more likely attracted by MNO offers, and the second group refers to customers that are more sensitive to added value and thus more likely attracted by MVNO offers. Each user is characterized by his perception of brand appeal and his perception of added value. Added value perception is modeled using a uniform distribution, while brand appeal perception parameter is considered binary. User utility is considered a linear function increasing in brand appeal and added value perception and decreasing in price. Authors provide a detailed analysis of operators' interaction and calculate operators' market share considering several scenarios.

Other studies ([6, 33, 34]) deem that MVNOs provide degraded Quality of Service (QoS), compared to the MNO, and should invest in content, in order to be viable and competitive in the market. The MVNO purchases resources from the MNO at wholesale price, and offers an added value to its services. They model the economic interactions between operators and provide the optimal strategies to increase their revenues. Similarly, Guijaro *et al.* in [13], model this interaction with a game-theoretical model. The bargaining and competition between operators are proved to be able to benefit both MNO and users, while the constraint for the MVNO to be competitive is improved technology deployment, compared to the MNO, which allows a more efficient use of the spectrum.

Unlike previous approaches, this thesis considers pricing strategies for both MNO and MVNO, in wholesale, and retail market, respectively. Moreover, the problem of conjoint price setting between operators is analyzed, and it is proved that cooperation in pricing development can benefit both operators, compared to blind competition. We demonstrate that user preferences can play a key role in pricing structure and profit maximization, by extension. We show that partial information may cause profit loss, but, due to the interaction between the operators, it is also possible to reap gain. To the best of our knowledge, there is no other study modeling MNO-MVNO interaction from this point of view.

2.2 Pricing Schemes

Wireless operators traditionally use flat rate, three part and two part tariffs, and usage based pricing to charge their subscribers. However, researchers have proposed several different charging strategies to explore new ways of matching revenues to costs. Several approaches suggest time dependent pricing in order to maintain/improve service quality, and avoid congestion on peak periods. Zhang *et al.* in [35] and Ha *et al.* in [36] evaluate time dependent pricing techniques, by simulations and a 50-user field study, respectively, and conclude that time-based pricing can benefit both operators and users. On operators' side, time-based pricing can improve bandwidth utilization and increase profit, while it can flatten temporal fluctuation of demand on peak hours, and prevent congestion. On users' side, time-dependent pricing may contribute to money saving, by enabling them to choose the time and volume of their usage.

Damasceno *et al.* in [37], claim that time-dependent pricing that does not take into account the topology of base stations may be unfair for users who are served from base stations with low workload during peak periods. Instead, authors propose, a time-depended pricing scheme that takes into consideration both time and the historic workload of each base station.

In an attempt to understand the effects of user behavior under flat rate tariffs, Blackburn *et al.* in [38], analyze a large data set of detailed usage information across voice, sms, and data services, combined with payment and cost information, obtained from an MVNO. They discover that 20% of the users consume more resources than what they pay for, and hence they are non-profitable for the operator. Thence, flat rate cannot be considered as an effective charging strategy. Furthermore, they empirically show that volume caps can increase the difference between revenues and traffic costs by a factor of two.

In this thesis, we propose a novel pricing scheme for networks with virtually unlimited capacity. Unlike approaches mentioned above, our pricing scheme is based on user preferences. More specifically, it is proved, by theoretical and simulation analysis, that the optimal pricing strategy, for an operator with a network of unlimited capacity, is based on users' WtPay characteristics. Operators usually collect information about user characteristics and preferences from surveys. Our team has developed the u-map, a Quality of Experience (QoE)-based geo-database recommendation tool for selecting the appropriate wireless provider based on user-specific criteria, such as cost and QoE [1,15–17]. The u-map employs the crowd-sourcing paradigm and collects network measurements and user profile data from mobile users in a geo-database. This profile includes information related to the user WtPay. Hence, it is straightforward that the u-map can be a valuable tool for providers to collect this information and contribute in pricing development.

2.3 Consumers' Behavior among Providers and Tariff Plans

Consumers' behavior under nonlinear pricing schemes has aroused the interest of scientists, especially in marketing and economics field. Lambrecht *et al.* in [39], obtain data usage records on DSL Internet access from a German Internet service provider over a five-month period, and develop a model of consumer tariff and usage choices under three-part tariffs. Their results show that demand uncertainty is a key driver of choice between three-part tariffs and steers consumers towards tariffs with high usage allowances. They also noticed that a large percentage of users does not select the optimal tariff plan, while most users consume much less service units than the tariff plan offer. Finally, uncertainty and variance in demand, increase the probability of choosing a flat rate tariff, and thus lead to higher costs for consumers, while on the other hand, contribute to increased revenue for operators.

In a similar way, Goettler *et al.* in [40, 41], highlight that consumers tend to have optimistic priors to flat fee tariffs. Approximately, half of the consumers do not select the tariff plan that minimizes their cost, while most of those who select the flat rate option have realized usage rates below the level for which the flat rate is optimal. Finally, they deduce that consumer uncertainty and switching costs enable operators to capitalize on consumers' bias.

Studies [42,43] examine the ability of subscribers to learn through consumption, and select the optimal tariff plan after their initial, possibly wrong choice. Researchers found that consumers are characterized by uncertainty, not only in their estimated traffic demand, but also in their future usage. Consumers do not seem to be biased for flat rate tariffs, and are likely to switch tariff options in an attempt to minimize their billing cost. However, consumers on flat rate tariffs learn at a slower rate about their usage, compared to those on measured plans.

Iyengar *et al.* in [44], incorporate consumers' uncertainty, consumption, and price, and propose a model that estimates both choice probabilities and usage levels for each consumer, as functions of service features, and different price components. Researchers validate their method with a field study of 72 students, and conclude among others, that consumption and rollover (the ability to carry on remaining voice minutes to the next month) add significantly to the utility of a wireless service, and, subsequently, to the probability of choice. They consider that charging influences consumption, and based on expected consumption for each consumer and choice probabilities, they find the optimal tariff plan, by evaluating all possible combinations of the design factors. Similarly, Huang in [45], attempts to estimate consumers demand under nonlinear pricing schemes, by combining monthly carrier-level aggregate output data with cross-sectional expenditure survey data. He considers a utility function that incorporates features, like consumption, price, add-on features, brand name appeal, ex-ante taste of the quality offered, received signal quality, and unexpected personal events, and tries to determine consumers' demand by maximizing the surplus of call making. In this work, he assumes that consumers select the optimal plan, i.e., the plan that maximizes their surplus. Both studies consider though only the voice service.

As far as customer loyalty and stickiness are concerned, Ascarza *et al.* in [46] conduct a 6-

month large scale experiment of 65000 subscribers of a cellular phone service, obtaining data from a company in south America. Their purpose is to assess how encouraging existing customers to switch to better plans affects their behavior and hence the firm's profitability. They indicate that firm being proactive and encouraging customers to switch to better tariff plans can harm firm's profitability. Encouragement might have a positive impact on customer satisfaction but can lower customer loyalty and inertia. It induces customers to feel regret, which has a negative impact on customer satisfaction and a direct effect on brand switching. In addition, subscribers realize how easy is to switch plans within the company and may also explore competitive offerings. They conclude that selecting the right customers to target is crucial, i.e., customers with low usage variability are more likely to accept the offer and less likely to churn if they reject it. Turel and Serenko, in [47], examine how user satisfaction, with wireless services, affects loyalty to a wireless service provider. They conduct an empirical study of 80 cellular subscribers in Canada and measure user satisfaction based on the American Customer Satisfaction Model (ACSM), a formula that measures the quality of goods and services as experienced by consumers and gauges their actual and anticipated consumption experiences. They found out that ACSM can adequately describe the perception and behavior of mobile phone users, depicting that perceived quality and perceived value are the key factors affecting a person's perception of the quality of provided services. The perception of quality influences the extent of loyalty, indicating that highly satisfied customers tend to demonstrate a high likelihood of repurchase and higher tolerance to price increases by providers or price decreases by competitors.

To our knowledge, all studies considering users' uncertainty and traffic demand, take into account one service (voice or data), and analyze users' behavior towards this direction. Unlike these approaches, in this study the impact of uncertainty in traffic demand estimation is attempted to be evaluated, by taking into account all services subscribers use in wireless markets, namely voice, text, and data. We model a user population, where each user has specific demand for all three wireless services, and observe the differentiation of user expenses and choices among a variety of tariff plans, as uncertainty in traffic demand estimation increases. We have developed u-plan, a tariff plan recommendation system running on Android mobile devices, which informs users about their monthly demand for each service, and facilitates them on selecting the appropriate tariff plan. We evaluate the impact of u-plan, on users' welfare, and prove through exhaustive simulations that the actual knowledge on traffic demand enables users to select the cost minimizing plan, thus contributing to money saving.

2.4 Mobile Traffic Analysis

Understanding the characteristics of cellular data traffic is an important aspect of network design, traffic modeling, resource planning, and network control. There have been several works, trying to analyze and model wireless traffic. Call duration distribution and its parameters are estimated in studies [22, 23]. Using sample data, obtained from mobile networks, researchers analyze call duration, and attempt to fit it into well-known probability distributions. They conclude that log-normal, and truncated lazy contractor (TLAC), a truncated version of loglogistic distribution, are the most suitable distributions to model call duration. They have found that these distributions are more precise than exponential distribution, which is usually used to describe call duration. TLAC and lognormal distributions are very similar, but TLAC is less concentrated in the median, i.e., it has power law increase ratios both on its head, and on its tail. However, in [21], Willkomm *et al.* study the duration of mobile calls arriving at a base station during different periods and conclude that they are neither exponentially nor lognormally distributed, possessing significant deviations making them hard to be modeled. They verify that about 10% of calls have a duration of about 27 seconds that correspond to calls which the called mobile user did not answer and the calls where redirected to voice mail. This makes the call duration distribution to be significantly skewed towards smaller duration due to non-technical reasons. Finally, it is showed that the distribution has a “semi-heavy” tail with large variance, being more than three times the mean, which is significantly higher than that of the exponential distribution. Similarly, in [18], Filiposka and Mishkovski investigate the characteristics of smartphone traffic, by obtaining data from 18 smartphone users over a three-month period field study. The main result of their analysis is the high diversity in behavior of the observed users and their traffic patterns. A large portion of the analyzed characteristics shows high deviations around the averaged value, thus making difficult to model all users using a simplified model.

Approaches [19, 20] provide a detailed measurement analysis of network resource usage, by analyzing data obtained from large 3G cellular networks. Both studies mention that the largest amount of data traffic is created by a surprisingly small fraction of subscribers. This points to a significant imbalance of network usage among subscribers with few subscribers hogging the much of the network resource. Jin *et al.* in [19], make a further categorization of data users into four groups according to their (expected) total data usage per month: users with usage above 1GB, who referred as heavy users, between 100MB and 1GB, between 10MB and 100MB, and between 1MB and 10MB.

A common conclusion among studies that analyze wireless traffic demand is that this traffic is characterized by high heterogeneity. All studies observe an immense diversity among users and their traffic patterns. This results in high deviations, larger than the mean. Although wireless traffic cannot be accurately modeled, due to the significant variation in their patterns, heavy tailed distributions, such as the lognormal or the log-logistic distribution, seem to be more appropriate to model it. In addition, in [20], Paul et al. present a series of results derived from data traffic collected at the core of a nationwide 3G network during one week in 2007. In this work, Fig. 1(a) depicts the CDF of total traffic volume (in bytes) per subscriber per day. Dr. Paul had the courtesy to provide the raw data on which this diagram has been based. Given the numeric values of the CDF, using the fitting tools of matlab, we have tried to fit these data into known distributions. The most prevalent candidates are the log-normal and the log-logistic distribution. In Table 2.1 we present the appropriate distributions than can describe each type of traffic.

Table 2.1: Distributions for wireless traffic demand modeling

Traffic type	Distribution
Call duration (Minutes)	Lognormal, Log-logistic, Exponential
Data (MBs)	Lognormal, Log-logistic

Chapter 3

Background Research

New paradigms in both the wholesale and retail service markets are being formed and accelerated by technological advances (e.g., in networking, virtualization), the booming of content delivery, and regulatory changes on access and competition rules. These paradigms can enrich the roles of service providers, differentiate traditional pricing schemes, and enable new business models. For example, cost reductions and higher efficiency can be achieved through increased multiplexing due to the pooling of existing infrastructure, resource sharing, crowdsourcing, and partnerships among providers.

The advances in wireless and sensor networks, cloud services, and smartphones have enabled the monitoring of large-scale dynamic environments and real-time data analysis. The Crowdsourcing and participatory sensing in large-scale systems provide the capability to monitor, in real time, the *quality of service* (QoS), as well as to estimate and predict the perceived *quality of experience* (QoE). Based on this information, personalized recommendations can be provided to customers for the appropriate services according to their profiles. Moreover, smart data analytics can enable service providers to improve their services. This chapter focuses on telecommunication markets, although these issues are also relevant in a plethora of other application domains and markets.

According to forecasts, in the following years, mobile data traffic will exceed several exabytes per month worldwide, while by 2016, video will be approximately 86 percent of the global consumer traffic [48]. Moreover, the relationships between users and providers are becoming more flexible. These changes will make their decision processes more complex. At the same time, the Body of European Regulators for Electronic Communications (BEREC) in recent reports envisages measures for *consumer empowerment*, boosting *consumer choice*, *network transparency*, and developing mechanisms for *data collection* and *analysis*. Towards the same direction are also national regulatory authorities, such as FCC, EETT, and Ofcom, in USA, Greece, and UK, respectively. Operators are required to choose a more rigorous approach, increase operational efficiency, and roll out new services in a cost-effective manner. By providing meaningful feedback to customers and providers, the performance of telecommunication markets can be significantly improved in terms of QoE, revenue, and social welfare.

These trends motivated the research in analyzing telecommunication markets. Specifically, the mobile computing group has developed the u-map [15–17], a user-centric reviewing system that enables users to monitor various services (running on smartphones) and collects user opinion scores about their performance (Fig. 3.1). These data are uploaded on a geo-database in a crowdsourcing manner. Data analytics can then be applied for customer profiling, new service planning and testing, pricing, and market refinements. The u-map informs users about the estimated performance of various services. Providers can also access the u-map to obtain network measurements about their infrastructure and user feedback about their coverage/services performance to potentially improve/adjust their deployment and services. Thus, the u-map can act as an "early-warning" and churn-avoidance mechanism. It also allows them to gain better knowledge about their customers and their QoE criteria, and assess their strategic network planning, pricing decisions, and service deployment strategies at a finer spatial granularity. The u-map can also provide feedback about possible compatibility issues of the device, in the context of a service, and their impact on the user experience, allowing the manufacturer, platform/OS developer, and service provider to identify potential problems early and constantly improve their products. Via the u-map, regulators can detect whether operators comply to certain specifications. Thus, the u-map can become a powerful tool to users, providers, operators, and regulators, introducing a paradigm shift in wireless access markets. Moreover, the team has developed CoRLAB [49,50], a

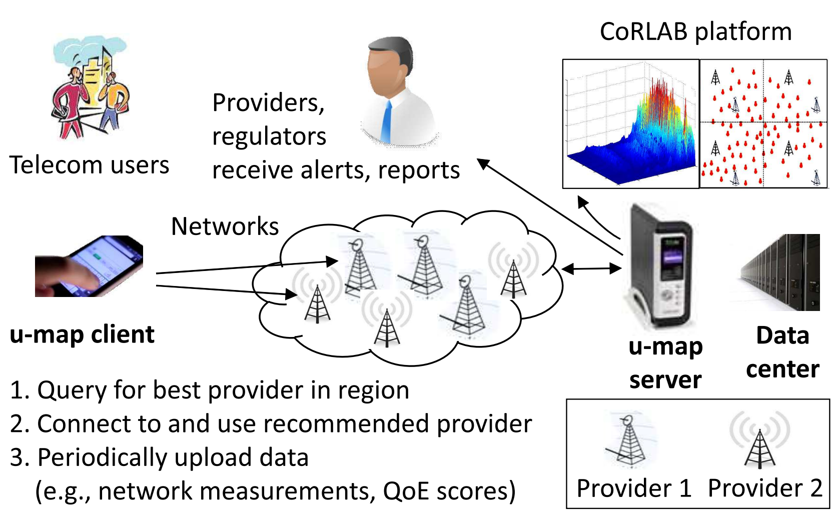


Figure 3.1: Example of the use of the u-map in telecommunication markets: users select the best provider/service, while providers receive reports about potential network failures [1].

modeling framework and simulation platform to analyze the evolution of telecommunication markets and services under a diverse set of customer populations and network conditions. In general, the analysis of such markets either adopts agent-based simulations (e.g., [11]) or employs macroscopic models that consider an average behavior of various entities (e.g., [51]). Moreover, such approaches rarely incorporate user-centric data or models in real time. In response, CoRLAB provides a modular multilayer framework, including models at multiple levels of detail: microscopic models that describe each distinct entity (e.g., user) as well as mesoscopic or macroscopic models based on aggregations of entities (e.g., homogeneous user populations). Furthermore, the u-map feeds CoRLAB with real-time or semi-real-time data about users and QoE feedback about the received services.

3.1 U-map

The u-map [15–17] is a recommendation system running on smartphones that follows the client-to-server architecture. In a crowdsourcing manner, it collects various objective and subjective measurements that indicate the performance of a certain service. These measurements are regularly uploaded on a spatio-temporal geo-database and processed by the u-map server. Based

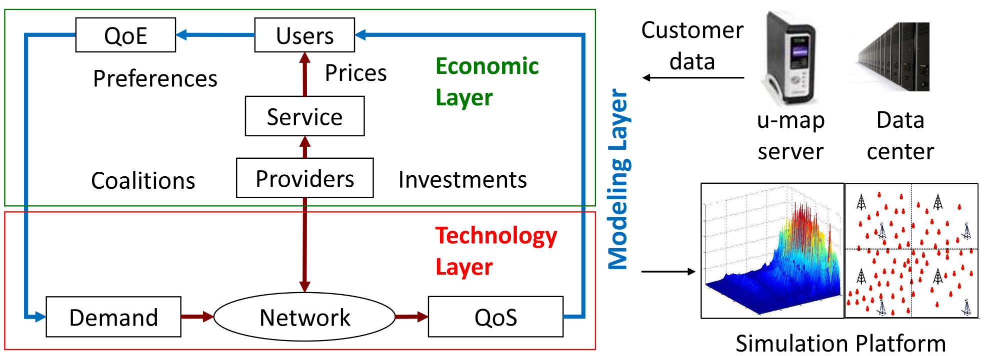


Figure 3.2: CoRLAB is integrated with the u-map. It can model and simulate markets using data provided by the u-map [1].

on this information, the u-map server can then provide user-centric QoE feedback and recommendations about the availability and performance of the provided services within a region. In addition, CoRLAB obtains these measurements from the u-map server (Fig. 3.2), and provides various geo-statistics about the evolution and performance of these services. To cope with large user populations, the u-map can be developed as a cloud service. The key modules of the u-map architechure include the monitoring, data analytics, QoE modeling, as well as privacy and access control.

3.1.1 Monitoring

Monitors have been developed for user devices or network infrastructures. For example, monitoring tools may collect various network measurements (e.g., Portolan [52]) or physical-layer information to enable the detection of spectrum availability/usage, whitespace, and interference [53]. The reliability of the measurements and security are significant aspects that need to be addressed. The monitoring tools should not compromise the user privacy. Monitoring on mobile devices needs to also address the energy cost and dependencies on the hardware, while monitoring at the infrastructure, the deployment cost. In the context of the u-map, monitoring can be performed at the user mobile devices, as well as at various gateways. The u-map data collection departs from state-of-the-art techniques in the following manner: unlike existing tools, which focus on specific network measurements [52, 53], the u-map obtains and correlates a rich set of multi-sourced data with QoE feedback (opinion scores) and geographical information. The collected data can be active or passive cross-layer QoS measurements, user demand statistics, and user preferences. The measurements are uploaded to the u-map server data repository for analysis (e.g., user profiling, QoE inference).

Extensive monitoring and data collection can improve the accuracy of the performance estimates, but also increase the energy consumption and detection delay, as the network interfaces need to monitor the channel over longer time periods and then send this information to the u-map server. The u-map can employ advanced signal processing and data mining techniques to determine the appropriate spatio-temporal granularity in the sampling process, and address the accuracy, privacy, and energy constraint trade-offs. The identification of the appropriate parameters that need to be analyzed in order to characterize the specific condition of interest is an important first step in the monitoring process. This determines at which layers and network points and at which spatio-temporal granularities the monitoring needs to be performed. The following subsection provides input about these aspects.

3.1.2 Data Analytics

The user profiling, clustering of user population, QoE modeling, geo-statistics, and warning generation are the primary objectives of the data analytics. Prior to data analysis, a sanitization treatment needs to be performed, since the collected measurements can be noisy, of high dimensionality, erroneous, and sparse. The data sanitization module detects erroneous entries, misconfigured/malicious data sources, and missing values. The statistical analysis method for treating these issues depends on the specific application characteristics, objectives, and requirements.

The user profile "integrates" a number of parameters associated with user preferences, requirements, demand, constraints, and capabilities with respect to services and context. For example, it may include information about the user's WtPay, data rate, traffic demand, QoE requirements, feedback consistency, and device characteristics. User profiling can be performed at different levels of detail, which may then impact the computational complexity of the follow-up market analysis. For example, an aggregate-level approach ignores specific individual user aspects and develops general, often less detailed, macroscopic models. On the other hand, a user-centric approach takes into consideration fine-level user information, aiming to form detailed profiles of individual users. A third approach employs clustering algorithms to determine homogeneous user populations and find representative user profiles for each population. Related to user profiling is QoE modeling, which is discussed in more detail in the following subsection.

The spatio-temporal analysis focuses on the geographical and temporal distribution of specific features or metrics, identifying the locality and evolution/spreading of various phenomena. Examples include the analysis of user workload (e.g., amount of traffic, flow arrival process, interactivity model, application, and usage pattern). The u-map can provide an early-warning mechanism that appropriately notifies users, providers, and regulatory authorities about various failures or deficiencies, reducing maintenance costs (e.g., when certain conditions on QoE and traffic load hold). Understanding how user behavior and expectations change depending on the context (e.g., network topology, network conditions, device/technology characteristics, mobility, location, and environment) is challenging, and the performance of empirical-based modeling studies is required.

3.1.3 QoE Modeling

Network benchmarks, such as jitter, latency, and packet loss, have been extensively used to quantify network performance. The evaluation of their impact on the user experience has received a lot of attention from the research community. Especially in the case of highdimensional measurements, it becomes important to understand which network metrics have a dominant impact on the performance of certain applications, distinguish the conditions that substantially degrade the performance of a given application, and investigate the predictability of these conditions.

The QoE is influenced by a diverse set of technical (e.g., QoS and device features), socio-economic (e.g., social network, advertisements, and brand name), human-related (e.g., sentiment and age), business (e.g., pricing, and WtPay), and contextual (e.g., time and location) factors [54], some of which are difficult to capture and model. For example, important parameters for VoIP are call setup time (i.e., time from the call initiation request to the beginning of the call), mel-frequency cepstral coefficients (MFCCs) for audio quality measurement, roundtrip time (RTT) statistics, packet loss ratio and burstiness, jitter, and number of retransmissions. For video streaming, important parameters include the playback quality (i.e., the bit rate being delivered), startup delay (i.e., time between the user clicks on the play button to the time the video starts playing), buffering ratio (i.e., the percentage of the session duration spent in buffering state) and rate adaptation/temporal dynamics (i.e., change of the rate during the session), RTT statistics, packet loss ratio, jitter, and number of retransmissions. Parameters to be measured for web browsing include page load time (i.e., the difference between the time the URL is requested from the browser and the time the objects are fetched) and lower-layer metrics, such as DNS lookup time, RTT, and TCP retransmission rates. To make the study amenable to theoretical analysis, QoE is usually expressed through simplified utility functions with nice mathematical properties that consider only a subset of these parameters. For instance, E-model [55] and PESQ [56] have been used for modeling the QoE in VoIP. Based on network measurements and subjective feedback collected via the u-map, this research aims to develop user-centric QoE models that can accurately reflect the user perspective for various services considering different techno-economical factors.

Classification and regression methods based on machine learning, data mining, and statistical modeling algorithms have also been employed for the prediction of QoE [57, 58]. The u-map applies a number of state-of-the-art machine learning algorithms, develops and trains models based on the collected network measurements and user feedback, and *dynamically* selects the best one for predicting the QoE in a user-centric manner. A longer-term objective is the inference of QoE without necessarily user intervention or feedback.

3.1.4 Privacy and Access Control

Any time data is shared with a third party, there is a potential for abuse. Therefore, a great deal of effort has been made to design privacy protection techniques for publishing anonymized records. Even though data sharing can be beneficial, users have privacy concerns and value these benefits differently. For example, some may prioritize anonymity, while others may be willing to share data unconditionally, with most users falling somewhere in between.

To protect user privacy, the u-map requires authorization for granting access to the database. The client-to-database connection relies on end-to-end security that protects the integrity and confidentiality of the submitted data by leveraging standard technologies (e.g., public-private key pairs, TLS). For further protection of sensitive information, like user location, access is allowed only to aggregate statistics. Obfuscation approaches (e.g., spatial/temporal cloaking) could also protect user location privacy at the cost of degrading the user experience. For example, if it is assumed a high level of user privacy, the responses of a location-based service would be inaccurate or untimely. Last but not least, the u-map provides a user-centric access control module that allows users to control the information revealed to third parties through a fine-grained discretionary approach. More precisely, access control rules define *who* has access to *what* data, *who* can be a user or another role (e.g., operator, application), and *what* is a query over the data. *Query rewriting* is then applied, “injecting” the access control rules into the request so that the rewritten request filters out the inaccessible data.

3.1.5 Development

The main functionalities of the u-map have been developed, and a pilot testbed has been deployed. Using this testbed, was performed a field study with real users and evaluated the impact of the u-map on the user experience in the context of a VoIP service [15]. Based on the collected data, it is also modeled the QoE for VoIP.

3.2 CoRLAB

Unlike traditional markets, emerging ones are larger (in the number of users and providers), more heterogeneous (in terms of services), and more complex and dynamic (e.g., in the interactions of providers and clients, and their decision making). Modeling such markets is challenging due to a plethora of business, network, and service-related phenomena that manifest at different spatio-temporal scales. Furthermore, the computational and scalability issues when analyzing such markets for long time periods or at a nation-wide level are prominent. The modeling approaches can be classified into two general categories, the microscopic- and macroscopic-level ones. Microscopic-level approaches model each entity, and its interactions with other participating entities, at a fine level of detail. However, due to the high computational complexity, they typically assume a limited number of such entities [11, 59]. On the other hand, macroscopic level approaches model the average behavior of certain types of entities (e.g., user population, service infrastructure) to make the analysis more tractable [51]. However, in many cases they result in inaccuracies and suboptimal performance.

In response to these challenges, CoRLAB, a modeling framework for large-scale diverse and dynamic markets, has been developed. In contrast to the previous approaches, which are either purely microscopic or macroscopic, CoRLAB is a complete multi-layer framework that allows the instantiation of a market at multiple levels of detail. At the microscopic level, the various entities are modeled in fine temporal and spatial detail, while at the macroscopic level, entities are described as a homogeneous population. Between these levels, various mesoscopic levels are defined in which entities are grouped in clusters. In a "coarse-grained" procedure, which results in a loss of information in a controlled and hierarchical fashion, the individual entities of the microscopic level (e.g., users) are replaced by clusters with certain attributes, computed based on data mining algorithms. Instead of modeling the decision making of each distinct user, the mesoscopic levels consider a number of user clusters, significantly reducing the computational complexity. Then, based on the requirements of a specific study, the appropriate mesoscopic level that achieves the desired trade-off between accuracy and complexity can be selected.

CoRLAB incorporates an economic and a technology layer (Fig. 3.2). At the economic layer, the decision making of providers and users is modeled using game theory, while at the technology layer, the QoS is estimated using appropriate queuing theoretical models. The QoS metrics and the prices offered by providers are translated through appropriate utility functions to an expression of the user QoE. For the selection of the input parameters of the queuing theoretical models and the parameters of the user utility functions, the contribution of the u-map is important since it reflects what happens in actual markets.

The mathematical models in CoRLAB are selected in such a way that they can be studied analytically. However, there are some markets of interest that, due to their inherent features, are analytically intractable. In these cases, CoRLAB employs empirical game theory, a recent research direction, to analyze these markets via simulations. The efficiency of this methodology strongly depends on the computational complexity and accuracy of the simulator and the selection of the appropriate mesoscopic level.

CoRLAB has been used to evaluate two scenarios: i) a telecommunication market that offers traditional subscriptions and the "flex service," a novel service that allows users to select their providers dynamically, and ii) a telecommunication market that supports mobile network virtualization. The next sections discuss the outcome of this analysis.

Chapter 4

Pricing for Mobile Virtual Network Operators

The mobile traffic growth is a catalyst of further technological advancements, and evolution in wireless access markets. The global mobile data traffic will increase 11-fold between 2013 and 2018, a compound annual growth rate of 61% [2]. At the same time, wireless communications change in a fast pace from the network operators' and service providers' perspective [60, 61]. However, not only the networks, but also the business models of the communication services over these networks change. In particular, network virtualization [25], a relatively new concept, allows network operators to lease parts of their network. In this context, Mobile Virtual Network Operators (MVNOs) may now find a new, vital space to flourish. MVNOs do not own a network infrastructure, but lease access in the wholesale market from a Mobile Network Operator (MNO), and resale access services in the retail market.

Typically, MVNOs target specific user populations, services, and regions, such as low-WtPay users (e.g., with low charge-per-month offers), customers on its own network (e.g., with free minutes and sms for its subscribers), youngsters (e.g., with unlimited sms, voice minutes over the same network), web users (e.g., with only data offers), ethnic (e.g., special offers for calls to specific destinations), and roaming users (e.g., calls, data). MVNOs tend not to compete directly with their host MNO, or with MNOs in general. Rather, they aim to widen, and deepen the market through brand appeal, targeting toward niche markets, and alternative distribution channels. The consumer-welfare impact of MVNOs is in offering extended and innovative services as opposed to lower prices [26]. While some countries have many MVNOs, typically only three in each country have the majority of MVNO customers [27]. Moreover, the combined MVNO market share per country is less than 10% [27].

This work focuses on the economics of MVNOs. In particular, we study the pricing model of MVNO in the retail market, and the charging scheme of MNO in the wholesale market. Furthermore, we are interested in assessing the impact of the knowledge about user profile on the profit of MVNOs and MNOs. Operators collect such information mostly from surveys. Our team has deployed the u-map, a QoE-based geo-database recommendation tool for selecting the appropriate wireless provider based on user-specific criteria, such as cost and QoE [1,15–17]. In this chapter, we examine how service providers, and network operators can take advantage of the u-map to design their charging strategies, and improve their profit.

4.1 Objectives

We aim to investigate the optimal pricing strategy for an MNO and an MVNO that interact in a wireless market, and to evaluate the contribution of the u-map towards this direction. Specifically, we target to develop alternative pricing techniques, by exploiting knowledge about user characteristics and preferences, obtained by the u-map. We are also interested in examining the possibility of cooperative interaction between operators, and evaluate under which conditions cooperation can contribute positively to their profit. We are proving that the u-map can play a key role on charging design, contributing to new pricing techniques, which can be profitable for both operators. It is also shown that cooperation between providers can be more profitable, compared to blind competition.

4.2 Assumptions

In our study, we assume a retail market where an MVNO sells mobile services to a set $\mathcal{I}$ of end users ($i \in \mathcal{I}$). We consider that the MNO owns a network of unlimited capacity, and it is active in wholesale market, i.e., it charges MVNO for the traffic served through its network. Each user i is assumed to have traffic demand d_i (in MB/month), which is independent and identically distributed random variable with cumulative distribution function (CDF) $F_d(x)$, and corresponding probability density function (PDF) $f_d(x)$. The WtPay for a certain service of a user is denoted as p_i^{max}. WtPays are also modeled as independent and identically distributed random variables with CDF $F_{p^{max}}(x)$, and PDF $f_{p^{max}}(x)$.

4.3 Pricing for MNO and MVNO

4.3.1 Pricing Scheme

In the retail market, MVNO employs a pricing scheme $p(\cdot)$, and charges each end user with $p(d_i)$. From user's side, if the user is willing to pay the amount charged with, he/she pays and receives the service; otherwise, he/she abstains. Formally, the user receives service if $p(d_i) \leq p_i^{max}$ or, equivalently, $\Theta(p_i^{max} - p(d_i)) = 1$, where

$$\Theta(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

is the Heavyside step function.

4.3.2 Wealth Share for MNO and MVNO

The total revenue that MVNO collects from the market ($R_V(p)$) can be derived as:

$$R_V(p) = \sum_{i \in \mathcal{I}} p(d_i)\Theta(p_i^{max} - p(d_i)) \tag{4.1}$$

whereas the traffic demand served:

$$D(p) = \sum_{i \in \mathcal{I}} d_i \Theta(p_i^{max} - p(d_i)) \tag{4.2}$$

Since MVNO does not own a network but leases it from an MNO in the wholesale market, MNO charges MVNO with $c(D)$ and its total profit is: $P_N(p,c) = c\Bigg(\sum_{i \in \mathcal{I}} d_i \Theta(p_i^{max} - p(d_i)\Bigg)$, or equivalently:

$$P_N(p,c) = \sum_{i \in \mathcal{I}} c(d_i)\Theta(p_i^{max} - p(d_i)) \tag{4.3}$$

where c is a linear function [38]. Consequently, the profit for the MVNO ($P_V(p,c)$) can be derived as the revenue collected from retail market ($R_V(p)$), minus the cost paid to the MNO ($P_N(p,c)$).

$$P_V(p,c) = R_V(p) - P_N(p,c) = \sum_{i \in \mathcal{I}} (p(d_i) - c(d_i))\Theta(p_i^{max} - p(d_i)) \tag{4.4}$$

Asymptotic Analysis

This work aims to study the share of wealth that MVNO and MNO can earn from the market at the infinity regime, where the number of users in the market tends to infinity ($I = |\mathcal{I}| \to +\infty$). The total wealth in the market is $W = \sum_{i \in \mathcal{I}} p_i^{max}$ and the wealth share for MVNO at the infinity regime can be derived as,

$$\frac{P_V}{W} \xrightarrow{\mathcal{I} \to +\infty} \frac{E((p-c)\Theta(p^{max} - p))}{E(p^{max})} = S_V^{\infty}(p,c) \tag{4.5}$$

Respectively, the wealth share for the MNO is,

$$\frac{P_N}{W} \xrightarrow{\mathcal{I} \to +\infty} \frac{E(c\Theta(p^{max} - p))}{E(p^{max})} = S_N^{\infty}(p,c) \tag{4.6}$$

where, for brevity, $p = p(d)$ and $c = c(d)$ and the expectation E is over all the involved random variables. The analytical calculation of the wealth share for MVNO and MNO is given in Eq. 4.7 and Eq. 4.8 respectively.

$$\begin{aligned}S_V^{\infty}(p,c) &= \frac{1}{E(p^{max})}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}(p(y)-c(y))\Theta(x-p(y))f_{p^{max}}(x)f_d(y)\mathrm{d}x\mathrm{d}y \\ &= \frac{1}{E(p^{max})}\int_{-\infty}^{+\infty}\int_{p(y)}^{+\infty}(p(y)-c(y))f_{p^{max}}(x)f_d(y)\mathrm{d}x\mathrm{d}y \\ &= \frac{1}{E(p^{max})}\int_{-\infty}^{+\infty}(p(y)-c(y))[1-F_{p^{max}}(p(y))]f_d(y)\mathrm{d}y = \int_{-\infty}^{+\infty}G_{p^{max}}(p,c)f_d(y)\mathrm{d}y \end{aligned} \tag{4.7}$$

$$\begin{aligned}S_N^{\infty}(p,c) &= \frac{1}{E(p^{max})}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}c(y)\Theta(x-p(y))f_{p^{max}}(x)f_d(y)\mathrm{d}x\mathrm{d}y \\ &= \int_{-\infty}^{+\infty}K_{p^{max}}(p,c)f_d(y)\mathrm{d}y\end{aligned} \tag{4.8}$$

where $G_{p^{max}}(p,c)=(p-c)\frac{1-F_{p^{max}}(p)}{E(p^{max})}$ and $K_{p^{max}}(p,c)=c\frac{1-F_{p^{max}}(p)}{E(p^{max})}$.

Wealth Share Maximization

MVNO aims to maximize its wealth share given the wholesale price. To achieve this, it is sufficient to maximize $G_{p^{max}}(p,c)$ with respect to p. Formally, if p^* is the optimal price scheme that maximizes the wealth share of MVNO, it holds that,

$$[1-F_{p^{max}}(p^*)]-(p^*-c)f_{p^{max}}(p^*)=0 \tag{4.9}$$

$$2f_{p^{max}}(p^*)+(p^*-c)\frac{\mathrm{d}f_{p^{max}}}{\mathrm{d}p}\bigg|_{p=p*}>0 \tag{4.10}$$

Similarly, MNO also tries to maximize its wealth share by means of maximizing $K_{p^{max}}(p,c)$ with respect to c. Contrary to MVNO, which cannot control the wholesale charge c (considered constant), MNO can affect the retail price p, which is now considered as a function of c. Consequently, if c^* is the wholesale charging scheme that maximizes MNO's wealth share, it holds that,

$$[1-F_{p^{max}}(p(c^*))]-c^*f_{p^{max}}(p(c^*))\frac{\mathrm{d}p}{\mathrm{d}c}\bigg|_{c=c*}=0 \tag{4.11}$$

$$2f_{p^{max}}(p(c^*))\frac{\mathrm{d}p}{\mathrm{d}c}\bigg|_{c=c^*}+c^*\frac{\mathrm{d}f_{p^{max}}}{\mathrm{d}p}\bigg|_{p=p(c^*)}\left(\frac{\mathrm{d}p}{\mathrm{d}c}\bigg|_{c=c^*}\right)^2+c^*f_{p^{max}}(p(c^*))\frac{\mathrm{d}^2p}{\mathrm{d}c^2}\bigg|_{c=c^*}>0 \tag{4.12}$$

Assuming that MVNO has selected its optimal pricing as of (4.9), then from (4.9) and (4.11), it follows that,

$$p^*(c^*) - c^* \left(1 + \frac{\mathrm{d}p^*}{\mathrm{d}c} \bigg|_{c=c^*} \right) = 0 \tag{4.13}$$

From the previous analysis, it is clear that if both operators aim at maximizing their wealth share, their pricing policies at the wholesale and the retail market depend only on the distribution of users' WtPay. This conclusion is rather expected since, in the absence of any limitation on the capacity of the network, the only constraint imposed is users' WtPay. Operators tune their pricing schemes so as to reap the maximum wealth share independently from the traffic generated by each user. To a certain extend, the assumption of unlimited capacity can be supported by the constant growth of the networks and the technological advancements in this field that tend to provide a "virtually" unlimited capacity. This conclusion is also in accordance with the latest trend of unlimited allowance tariff plans in the mobile communications market.

4.4 Performance Analysis

To gain further insight on the pricing behavior of both operators, we also examine the specific one, where the WtPay follows an exponential distribution with mean value μ [13]. Then, $F_{p^{max}}(x) = 1 - e^{-\frac{x}{\mu}}$ and $f_{p^{max}}(x) = e^{-\frac{x}{\mu}}/\mu$. From Eq. 4.9, we derive the optimal price scheme for MVNO as $p^* = \mu + c$, which also satisfies Eq. 4.10. It emerges that the pricing strategy of MVNO is to transfer the wholesale cost directly to the retail market, adding an extra charge upon the wholesale cost so as to earn profit. For MNO to maximize its wealth share, Eq. 4.13 must hold, which results that $c^* = \mu$, which also satisfies Eq. 4.12, thus $p^*(c^*) = 2\mu$. From equations (4.7) and (4.8), the maximum wealth share for MVNO and MNO is calculated as $S_V^{\infty}(p, c) = S_N^{\infty}(p, c) = e^{-2}$. As a result, MVNO and MNO equally share the profits reaped from the market.

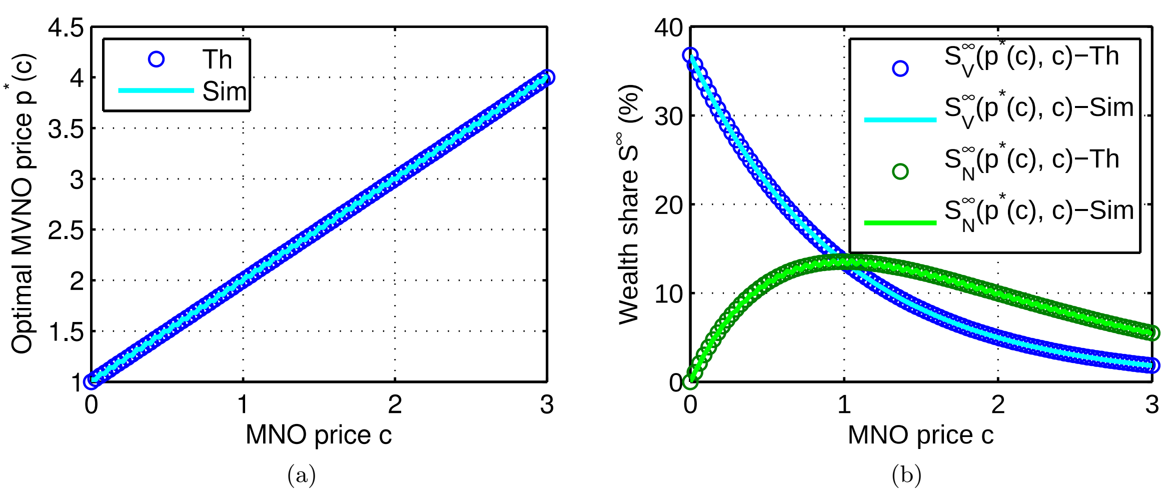


Figure 4.1: (a) Optimal MVNO price $p^*(c)$ and (b) wealth share for MVNO $S_V^{\infty}(p^*(c), c)$ and MNO $S_N^{\infty}(p^*(c), c)$ at optimal MVNO price $p^*(c)$ vs. MNO price c.

Additionally to the previous analysis, we have simulated a wireless access market with $\mathcal{I} = 10^7$

users, whose WtPay follows an exponential distribution with mean value $\mu = 1$. MVNO tunes its price p as MNO's price c varies. Thence, MNO selects the optimal wholesale price c^* given MVNO's pricing strategy $p^*(c)$. Fig. 4.1a depicts the price p^* for MVNO that maximizes its wealth share vs. the wholesale charge c of MNO. The wealth share for MVNO and MNO when MVNO employs its optimal price p^* vs. the wholesale charge c of MNO are presented in Fig. 4.1b. The simulation curves closely follow the analytical ones. Furthermore, the optimal wholesale charge is $c^* = \mu = 1$, which leads to $S_V^\infty(p^*, c^*) = S_N^\infty(p^*, c^*) = e^{-2} \approx 13.53\%$ (curve S_N^∞ in Fig. 4.1b).

4.4.1 The Value of Information

The previous section focuses on the price setting for MVNO and MNO under perfect knowledge of users profile. However, it is unrealistic to assume the availability of perfect knowledge about user profiles at MVNOs and MNOs. The partial knowledge collected based on current methods, such as surveys, may be inaccurate, biased, partial, and certainly costly. Furthermore, user preferences change dynamically in a fast rate so the available information quickly becomes obsolete. We assume the presence of a system, like the u-map, which can provide information about user preferences in an almost real time. Users feed their preferences to the u-map server/database, via the u-map client running at their smartphone. The u-map builds the user profile of each user. We now quantify the impact of this information on profit.

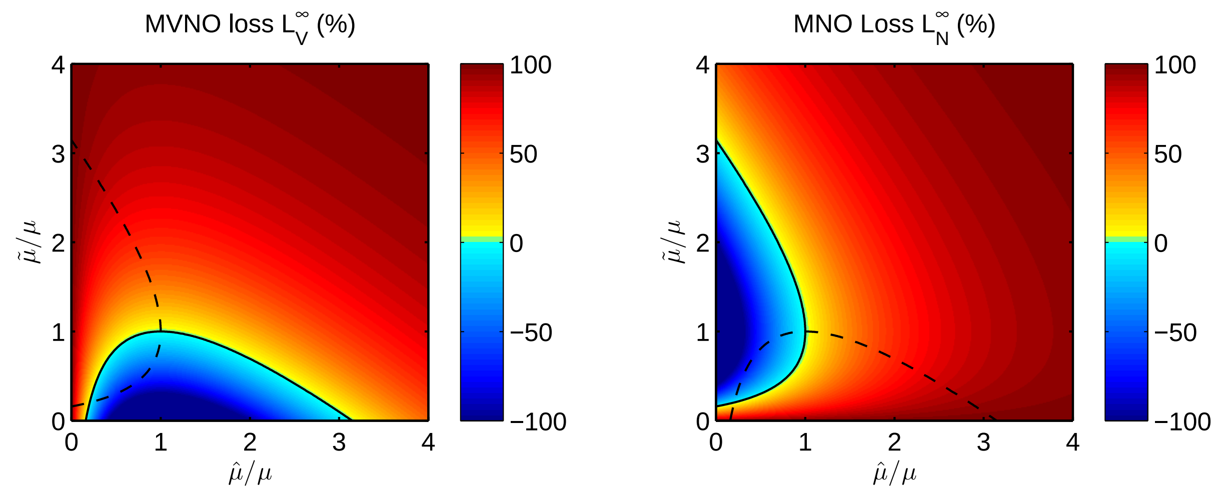
The MVNO and MNO gather information from a number of users in the market and estimate the parameters of the WtPay distribution. Assuming that the WtPay follows an exponential distribution with mean μ. MVNO and MNO act independently and estimate this mean value as $\hat{\mu}$ and $\tilde{\mu}$, respectively. This results that MNO maximizes its wealth share by setting $\tilde{c}^* = \tilde{\mu}$, whereas MVNO decides to charge end users with $\hat{p}^* = \hat{\mu} + \tilde{\mu}$. As a result, the loss that each one suffers (L_V^∞, L_N^∞) from this inaccurate estimation is as follows,

$$L_V^\infty = 1 - \frac{S_V^\infty(\hat{p}^*, \tilde{c}^*)}{S_V^\infty(p^*, c^*)} \overset{(4.7)}{=} 1 - \frac{\hat{\mu}}{\mu} e^{2-(\frac{\hat{\mu}}{\mu}+\frac{\tilde{\mu}}{\mu})} \tag{4.14}$$

$$L_N^\infty = 1 - \frac{S_N^\infty(\hat{p}^*, \tilde{c}^*)}{S_N^\infty(p^*, c^*)} \overset{(4.8)}{=} 1 - \frac{\tilde{\mu}}{\mu} e^{2-(\frac{\hat{\mu}}{\mu}+\frac{\tilde{\mu}}{\mu})} \tag{4.15}$$

The loss for the two operators is depicted in Figs. 4.2a and 4.2b. Interestingly, the loss can be positive or negative, i.e., there is loss or a gain from the inaccurate estimation of μ.

In particular, if both operators overestimate the WtPay of end users, i.e., $\hat{\mu} > \mu$ and $\tilde{\mu} > \mu$, they increase the retail and wholesale prices, driving thus more users to abstention from market. This results in loss for both operators ($L_V^\infty > 0, L_N^\infty > 0$). If one operator overestimates the WtPay whereas the other underestimates it, i.e., $\hat{\mu} > \mu$ and $\tilde{\mu} < \mu$ or $\hat{\mu} < \mu$ and $\tilde{\mu} > \mu$, the operator that underestimates WtPay charges less than optimal, so the loss in unavoidable. However, the fact that this operator charges less than optimal widens the profit gain for the other



(a) (b)

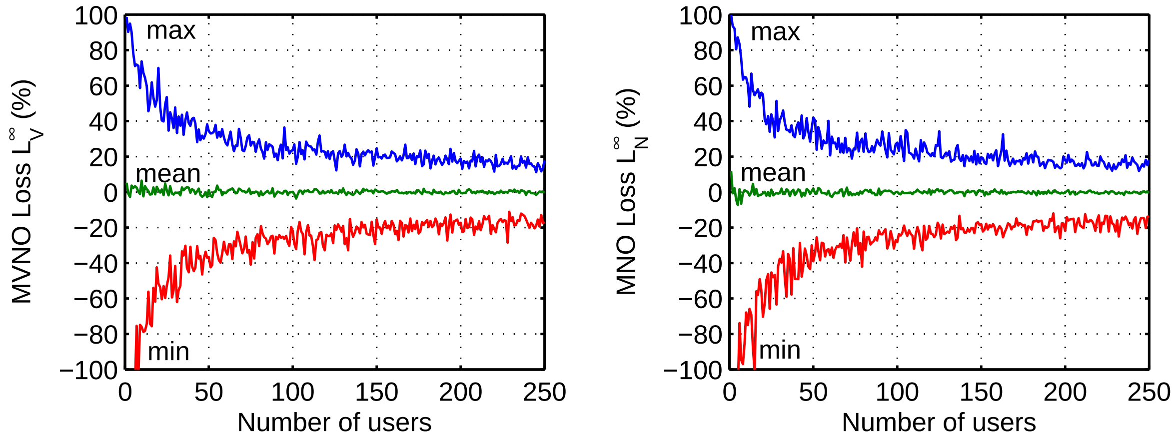
Figure 4.2: (a) MVNO and (b) MNO loss in wealth share due to inaccurate estimation of the WtPay distribution parameter (solid lines correspond to zero loss for the corresponding operator). MVNO and MNO estimate mean WtPay, actually μ, as $\hat{\mu}$ (x-axis) and $\tilde{\mu}$ (y-axis), respectively.

operator. In other words, the operator can now charge more. That is why the other operator has gain from the overestimation of WtPay, because it charges more than optimal. Of course, the overestimation is useful up to the point that $\hat{\mu} < -W_{-1}(-e^{-2})\mu$ or $\tilde{\mu} < -W_{-1}(-e^{-2})\mu$ for MVNO and MNO, respectively, where $W_k(\cdot)$ is the k-th branch of the Lambert W function ($W_{-1}(-e^{-2}) \approx -3.15$). From this point onward, the operator has consumed the advantage and loss follows.

The most interesting case is when both operators underestimate the WtPay, i.e., $\hat{\mu} < \mu$ and $\tilde{\mu} < \mu$. In the intersection of the zero-loss curves, both operators can have a gain (Figs. 4.2a and 4.2b). When $\hat{\mu} = \tilde{\mu} = \mu/2$, both operators gain $1 - e/2$ and their wealth share becomes $S_V^\infty(\hat{p}^*, \tilde{c}^*) = S_N^\infty(\hat{p}^*, \tilde{c}^*) = e^{-1}/2 \approx 18.39\%$. We observe that the competition does not allow the operators to explore a better operational point for both. By considering a "cooperation" between the MVNO and MNO, instead of blind competition, they could have increased their wealth share by 35.91% approximately. Finally, if the underestimation of WtPay falls below $-W_0(-e^{-2})\mu$ ($W_0(-e^{-2}) \approx -0.16$), both operators lower their prices that much that they cannot recover the loss (due to low price) from the increased user participation and loss again incurs.

We estimate the loss of MVNO and MNO as a function of the number of users employed for the estimation of the parameter of the WtPay distribution (Figs. 4.3a and 4.3b, respectively).

This experiment assumes $I = 10^7$ number of users in the market and $\mu = 1$. For each user population, we have conducted 100 estimations of μ, and present the maximum, mean, and minimum loss encountered by the operators for this sample size. These results confirm the findings of the previous analysis: the loss can be positive or negative for both operators. Although the mean value converges very fast to zero, more than 200 user profiles are required to ensure that the maximum loss remains below 20%. The u-map offers a timely, and cost-effective way to



(a)

(b)

Figure 4.3: Simulation results for (a) MVNO and (b) MNO loss vs. the number of users used for WtPay distribution parameter estimation.

collect this information.

Chapter 5

Tariff Plan Selection by Customers

Wireless operators typically offer their customers a choice among a variety of tariff plans. Price discrimination techniques, like flat rate, three-part, and two-part tariffs are widely used in telecommunication industry in an attempt to propose the best tariff plan for each subscriber. A three part tariff is defined by an access price, a usage allowance per service, and a marginal price for any usage in excess of the allowance, while a two-part tariff is composed of two parts, a fixed fee and a constant charge for each service unit. Flat rate tariff charges a single fixed fee for a service, regardless of usage.

Public at large is massively confused by mobile phone charging [62]. In modern wireless markets, operators offer multiple tariff plans to give their customers the opportunity to select the tariff plan that best suits to their traffic demand. The variety of tariff plans, the complex pricing structures, as well as uncertainty in demand, make tariff plan selection not trivial. Nearly, one in two consumers enrolls with the wrong tariff plan, and despite being able to change plans at any time, usually without penalty, many consumers remain on the "wrong" plan even after they have sufficiently revise their initial beliefs [41]. The probability of not selecting the optimal tariff plan increases with uncertainty, and users tend to select flat rate plans in an attempt to control their monthly bills and avoid usage shocks. This trend seems beneficial for providers, as users, by not selecting the cost-minimizing plan, tend to spend more for wireless services.

In this chapter, we will try to analyze the impact of inaccuracy on traffic demand estimation. We have developed u-plan, an application that runs on Android mobile devices and monitors wireless usage for all three available services (voice minutes, text messages, and data). Through our application, the user is informed about his monthly consumption and facilitated to select the optimal tariff plan, based on his usage patterns. We will try to investigate how perfect knowledge, in wireless traffic demand, affects tariff plan selection and what are the consequences on consumers' expenses and operators' revenue. The rest of this chapter is organized as follows: first, we briefly describe the basic components and functionalities of u-plan application. Then, we give a detailed description of our simulation platform and our input parameters. Finally, we present our results and provide a sensitivity analysis.

5.1 U-plan

U-plan is a tariff plan recommendation system that runs on Android mobile devices. It provides a simple and user-friendly graphical interface, where a user inserts his monthly demand per service, and his WtPay, and u-plan proposes the cost minimizing plan, by calculating the cost for all available tariff plans. U-plan offers also the choice of Automatic Usage Estimation. Setting this choice on, it estimates the mean monthly demand, by taking into account the consumption of previous months. Our application provides statistics on user's monthly traffic consumption on the main wireless services, namely voice, text, and data. U-plan provides the cost created for the user, from each available tariff plan and informs him about his consumption in each different service with charts. Finally, it informs the user about his closest contacts, i.e., those who communicates more often.

5.2 Objectives

Our main objective in this study is to evaluate the impact of inaccuracy in traffic demand estimation, on consumer economic benefit. Specifically, we aim to investigate the consequences of traffic demand uncertainty on user expenses and operators' revenue, and highlight the contribution of u-plan on user welfare. We are also interested in developing a modular simulation platform, that can model the economic aspects of a wireless market, by incorporating tariff plans and users with specific characteristics in traffic demand and WtPay. Each user is characterized by his traffic demand in today's most popular wireless services, namely voice, text, and data, and his WtPay, i.e., the maximum amount of money he is willing to pay to buy a tariff plan. In our study, we prove that u-plan can be highly beneficial for the users, as it informs them about their actual demand and proposes the cost minimizing plan.

5.3 Assumptions

The minimization goal of finding the cheapest tariff plan for a given level of traffic demand is quite simple to implement, but understanding and incorporating all problem parameters is considerably more complex. In Greek wireless market, there exist three wireless providers, namely Cosmote, Vodafone, and Wind. Each of the operators offers a variety of tariff plans in the market, with numerous and frequently different options, add-ons, and volume related discounts. The plans change about every six months, usually by adding new offers that make the existing obsolete.

In our study, we have considered a number of representative tariff plans of each wireless operator. We have included plans ranging from low, medium, and high price category, as well as prepaid and contract plans. Incorporating all plans with their add-ons and special offers would be very complex, but we also consider that it will not have significant effect to our study [**?**, 41]. All plans offer services, like voice minutes, sms, and data, while we haven't included plans that referred to special user categories (e.g., student offers). We assume that for voice and sms services, plans use price discrimination between networks, as commonly happens in wireless markets. The 72% of users' voice demand and 82.1% of text demand are within networks of the same network operator (on-net) [63]. Finally, we assume that users do not have bias on certain tariff plans, and choose correctly the cost minimizing plan, based on their estimated traffic demand. This, may not seem realistic, as users may have inaccuracy and bias, or may also take into account facts like brand name appeal and QoS of the respective provider, on tariff plan selection. In this study, however, we focus on the economic effects of inaccuracy in traffic demand estimation and we do not take these facts into account .

Each user is assumed to have a specific traffic demand in voice minutes, sms, and data (in MBs), and a maximum amount of money that offers to serve it (WtPay). Is assumed that a user, who cannot afford to buy a tariff plan, does not revise his demand, but abstains from the market. Each service is modeled with an independent and identically distributed (i.i.d.) random variable that follows a known distribution. Inaccuracy, in estimation of traffic demand, is modeled with additive white Gaussian noise (AWGN) of zero mean and specific standard deviation. Inaccuracy, in demand estimation for a service, is independent of inaccuracy in demand estimation for the remaining services, i.e., a user who underestimates the demand for a service may underestimate, or overestimate as well, the demand for the remaining services.

5.4 Methodology

Problem Definition: What are the consequences of inaccuracy in estimation of traffic demand? How much, does inaccuracy affect tariff plan choice and consumers' expenses, by extension? Can perfect knowledge of traffic demand be beneficial for users? We will try to answer these questions, by simulating a market, where users with specific wireless traffic demand in voice, text messaging (sms), and data (MBs), are offered a finite number of tariff plans and try to select the optimal plan, i.e., the plan that minimizes their cost. We evaluate user choices and expenses in different scenarios, by incorporating uncertainty in their estimation.

5.4.1 Market Model

We consider a wireless market of $\mathcal{I} = 10^6$ users, with traffic demand $T = \{V, Sms, MB\}$ in voice minutes, text messages (sms), and data (MBs), and specific WtPay. V, Sms, and MB are i.i.d random variables that follow well-known distributions. WtPay, for a user $i \in \mathcal{I}$, is denoted as p_i^{max}. Users are offered a set of tariff plans, $J = \{j_1, j_2, ..., j_N\}$, estimate their traffic demand, as $\hat{T} = \{\hat{V}, \hat{Sms}, \hat{MB}\}$, and select the tariff plan that minimizes their cost. The cost of selecting a tariff plan $j \in J$ for user i is estimated as,

$$p_{j,i}(T_i) = p_j^f + p_j^m(V_i - l_j^m)\Theta(V_i - l_j^m) + p_j^s(Sms_i - l_j^s)\Theta(Sms_i - l_j^s)+ \\ p_j^d(MB_i - l_j^d)\Theta(MB_i - l_j^d) \quad (5.1)$$

where

$$\Theta(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

is the Heavyside step function. The parameters of the cost function are declared in Table 5.1.

Table 5.1: Parameters of the cost function

Parameter	Description
$p_{j,i}$	Cost of selecting plan j for user i
p_j^f	Access fee of plan j
l_j^m	Allowance for voice minutes of plan j
l_j^s	Allowance for text messages (sms) of plan j
l_j^d	Allowance for data (MBs) of plan j
p_j^m	Price per minute for minutes over the allowance of plan j
p_j^s	Price per sms for messages over the allowance of plan j
p_j^d	Price per MB for MBs over the allowance of plan j
V_i	Demand for voice minutes of user i
Sms_i	Demand for text messages (sms) of user i
MB_i	Demand for data (MBs) of user i

Each user can select at most one tariff plan. Formally, user i will select the cost minimizing plan j of set J, only if $p_{j,i} \leq p_i^{max}$. If more than one tariff plans offer the same cost for a user, he will select one randomly. Finally, if a user cannot afford to buy any tariff plan, he remains disconnected.

Traffic Demand and WtPay

We assume that users' traffic demand follows a lognormal distribution. Lognormal, log-logistic, and exponential distributions are, according to the literature ([20, 22, 23]), the most suitable distributions to describe call duration and data demand. We suppose that these distributions can describe voice and sms demand as well. We select standard deviation to be slightly higher than the mean, thus modeling better user heterogeneity [18]. Mean values, for each variable, are drown from Greek National Regulatory Authority (EETT). According to EETT, mean values per subscription, by the end of 2013, were, approximately, 171 minutes, 38 sms, and 94 MBs per month for voice, text, and data usage, respectively [63].

We observe that access fee for tariff plans in Greek wireless market ranges from 2 to 91.35 euros (Table 5.3). We select WtPay to be in the feasible range of 10-100 euros, which can be considered close to the range of 15-90$ which has been emerged in [44] using survey data. We divide the population of our market into three groups, based on their WtPay, “low-WtPay”, “medium-WtPay”, and “high-WtPay” users. Typically, as with tariff plans, users with higher WtPay have increased traffic demand, compared to those with low WtPay. Hence, we consider as low-WtPay, medium-WtPay, and high-WtPay, users with budget ranging from 10-25, 25-60, and 60-100 euros, respectively.

Considering now a wireless market as depicted in Table 5.2, that consists of low-WtPay, medium-WtPay, and high-WtPay users, with population percentage 25%, 50%, and 25%, respectively. Users with higher budget have increased traffic demand, compared to those with lower, with the constraint that the average monthly demand of the whole market population meets the values of [63]. WtPay, for each user category, is drown from a uniform distribution in the ranges mentioned above.

Table 5.2: Market Characteristics

User Category	% of Population	WtPay (Euros)	Mean Monthly Traffic Demand		
			Data (MBs)	Voice (Minutes)	Sms
Low-WtPay	25%	10-25	25	55	10
Medium-WtPay	50%	25-60	75	140	30
High-WtPay	25%	60-100	200	350	80

Tariff Plans

The set J of tariff plans in our wireless market is drown from the three wireless network operators in Greek market, assuming *Operator_1*, *Operator_2*, and *Operator_3*. Each tariff plan of set J is a replication of tariff plans offered in Greek market, by wireless operators, by the end of 2014. Based on access fee, set J includes tariff plans of low, medium, and high access fee [44]. As low access fee tariff plans, we consider those with access fee in the range (2, 10), medium those in range (10, 40), and high those in range (40, 100). We have chosen a representative sample of 6 tariff plans from each operator. Tariff plans are depicted in Table 5.3. Tariff plans $Tariff\_1$ to $Tariff\_6$ belong to *Operator_1*, $Tariff\_7$ to $Tariff\_12$ to *Operator_2*, and plans $Tariff\_13$ to $Tariff\_18$ to *Operator_3*. Each tariff plan is defined by its access fee, which is the amount of money paid from subscriber to buy the tariff plan, the allowance of units for each service offered, and a marginal price per service unit for units that exceed the allowance.

The available services are voice, text, and data. For voice and text services, operators use a further differentiation between On-Network (on-net) and Off-Network (off-net) units. On-Network refers to the case when the caller/sender and the callee/receiver are both in the network

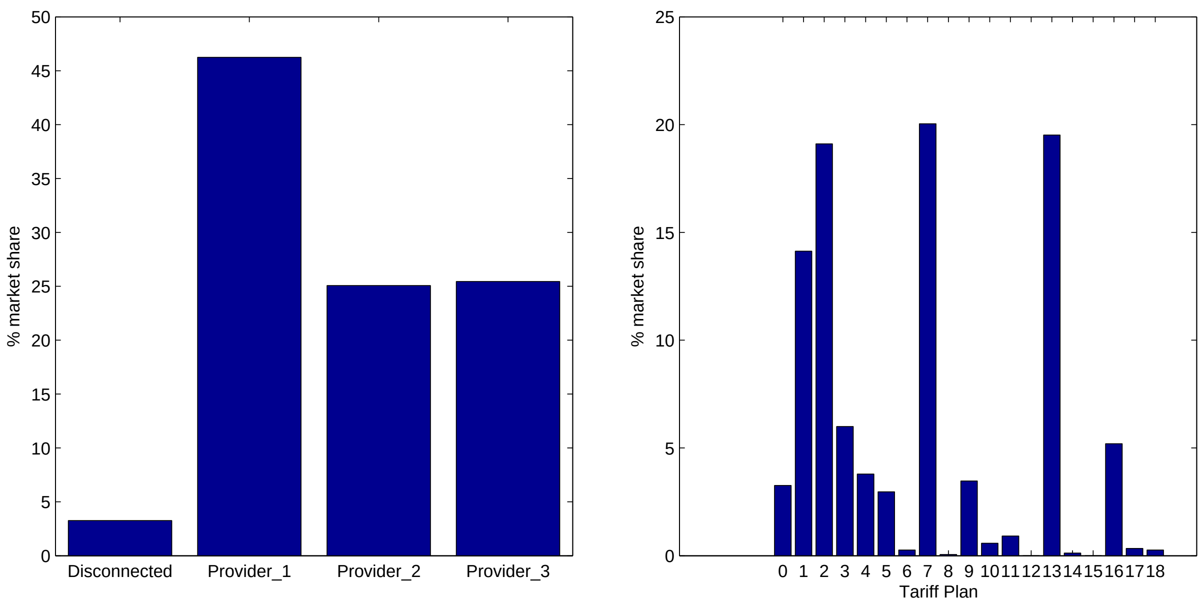
Table 5.3: Tariff Plans

Tariff Plan	Access Fee	Data (MB)	Voice Minutes		Sms		Charge over Allowance		
			On-net	Off-net	On-net	Off-net	MB	Minute	Sms
$Tariff\_1$	5	-	400	100	-	-	0.15	0.39	0.10
$Tariff\_2$	7	-	400	100	400	100	0.15	0.39	0.10
$Tariff\_3$	20	100	1500	30	1500	20	0.10	0.33	0.12
$Tariff\_4$	31.5	400	1500	120	1500	40	0.10	0.33	0.12
$Tariff\_5$	40.5	800	1500	180	1500	60	0.10	0.33	0.12
$Tariff\_6$	80	4000	-	3000	-	3000	0.10	0.33	0.12
$Tariff\_7$	3	30	300	-	300	-	0.16	0.39	0.10
$Tariff\_8$	7	-	500	100	-	-	0.16	0.39	0.10
$Tariff\_9$	26.5	100	1500	50	1500	30	0.02	0.37	0.14
$Tariff\_10$	31.5	300	-	400	-	40	0.02	0.37	0.14
$Tariff\_11$	40.5	300	-	700	-	70	0.02	0.37	0.14
$Tariff\_12$	91.35	1500	1500	580	1500	360	0.02	0.37	0.14
$Tariff\_13$	2	-	-	100	-	-	0.19	0.39	0.10
$Tariff\_14$	2	-	300	-	300	-	0.19	0.39	0.10
$Tariff\_15$	5	-	-	200	-	-	0.19	0.39	0.10
$Tariff\_16$	27	300	-	300	-	30	0.10	0.20	0.14
$Tariff\_17$	36	500	-	500	-	50	0.10	0.20	0.14
$Tariff\_18$	80	3000	-	3000	-	3000	0.10	0.20	0.14

of the same provider, while Off-Network refers to the case where one of the two belongs to the network of a different provider. Voice service is defined in minutes, text service in text messages (sms), and data service in MB, while all tariff plans have a monthly duration. According to [63], on-net voice traffic constitutes 72% of the total volume of mobile voice calls in 2013, while on-net sms traffic corresponds to 82.1% of the total traffic. We take this fact into account, in our charging scheme, and assume that 72% of voice minutes and 82.1% of text messages of each user are charged from on-net units, if a tariff plan makes this discrimination. The remaining demand is charged from off-net units. For tariff plans $Tariff\_6$, $Tariff\_10$, $Tariff\_11$, $Tariff\_13$, $Tariff\_15$, $Tariff\_16$, $Tariff\_17$, and $Tariff\_18$, which offer only off-net units, is noted that these units are for communication between subscribers of all available networks, thus users' total voice and sms demand is charged from off-net units.

5.5 Performance Analysis

Running the simulations in the market mentioned above, we observe how users are distributed among tariff plans and operators, how many of them stay disconnected, the money paid for tariff plan, and the wealth obtained from operators, as percentage of the total wealth exists in the market. As total wealth we consider the sum of WtPay for all users in the market. We can see users' distribution among providers and tariff plans in Fig. 5.1a, and Fig. 5.1b, respectively. Disconnected users are denoted with zero in Fig. 5.1b.



(a) (b)

Figure 5.1: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Perfect Knowledge" scenario.

We consider this scenario as "Perfect Knowledge" scenario, where users have precise knowledge of their usage, there is no uncertainty in estimation of their traffic demand, and thence, select the tariff plan with the minimum cost. We observe that the majority of users select a tariff plan to serve their demand, while there is a small percentage (≈3.25%) that remains disconnected. In this scenario, operators collect the 35.92% of total wealth. Fig. 5.2 presents the Empirical Cumulative Distribution Function (ECDF) of money paid (in Euros) for tariff plan along users. Users' mean cost for tariff plan, in "Perfect Knowledge" scenario, is 16.38 Euros.

We further try to evaluate the impact of uncertainty in traffic demand estimation. We insert uncertainty in users' estimation, with the form of AWGN of zero mean and observe user choices, as well as money paid for tariff plan for varying standard deviation (std). Users now select tariff plan based on their estimated traffic demand, but are charged based on their actual usage. We consider four new scenarios, "Uncertainty_50", "Uncertainty_100", "Uncertainty_200", and "Uncertainty_300", where users have inaccuracy of std 50, 100, 200, and 300 in estimation of

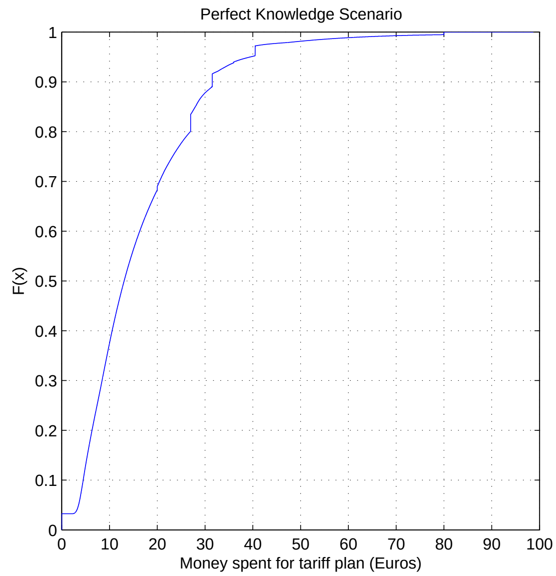
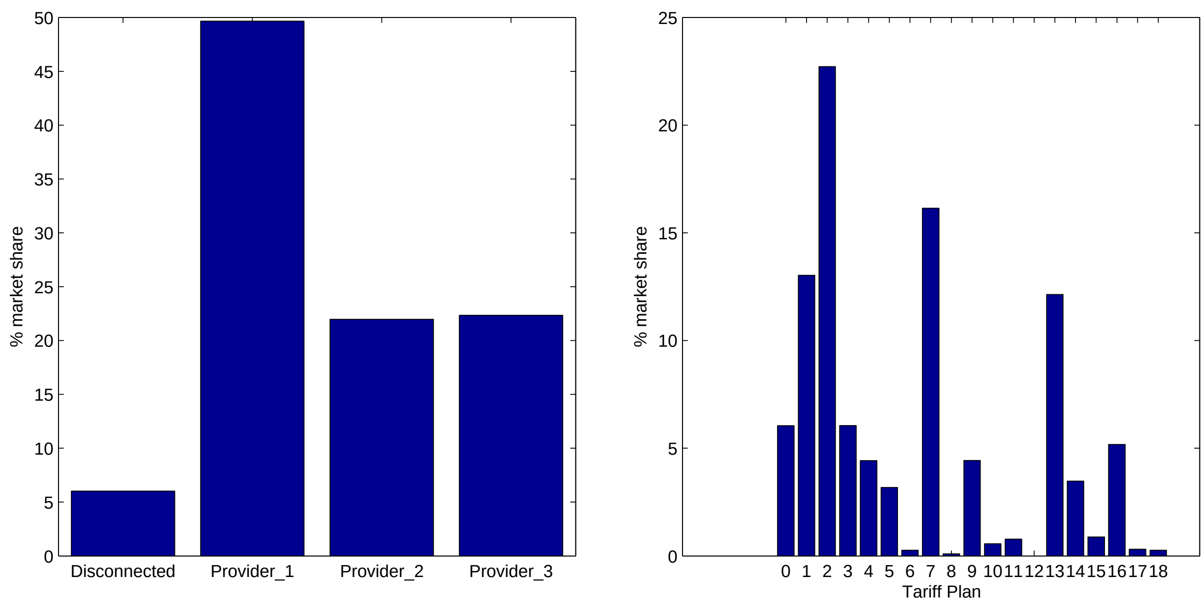


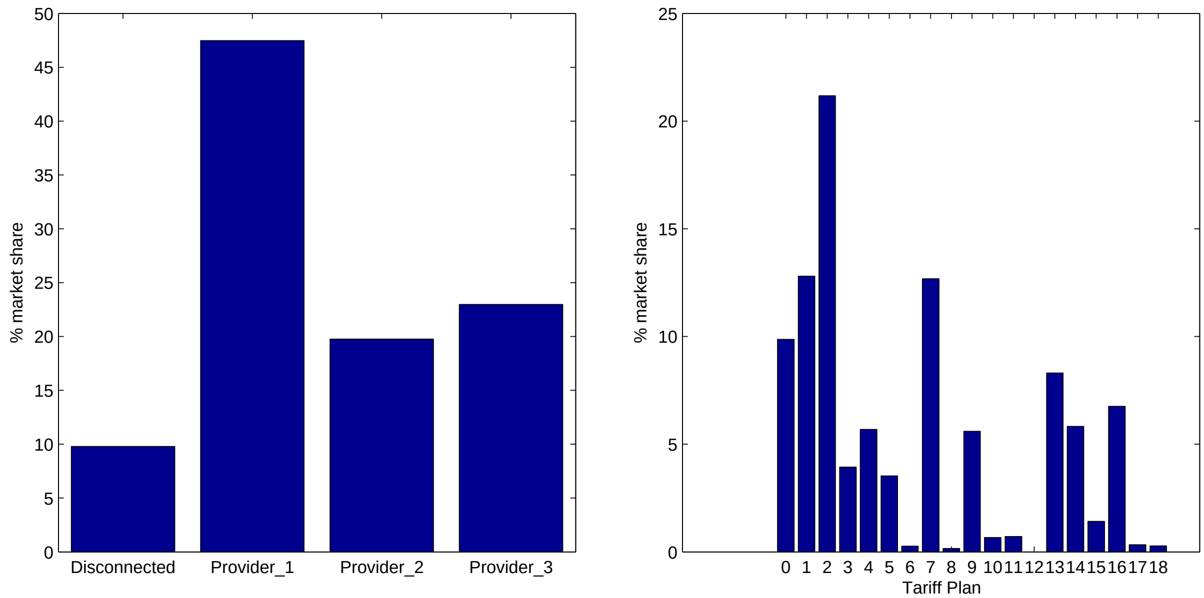
Figure 5.2: ECDF of money spent for tariff plan.

traffic demand for each scenario, respectively. Users' distribution among operators and tariff plans is depicted in Fig. 5.3, Fig. 5.4, Fig. 5.5, and Fig. 5.6 for scenarios "Uncertainty_50", "Uncertainty_100", "Uncertainty_200", and "Uncertainty_300", respectively.



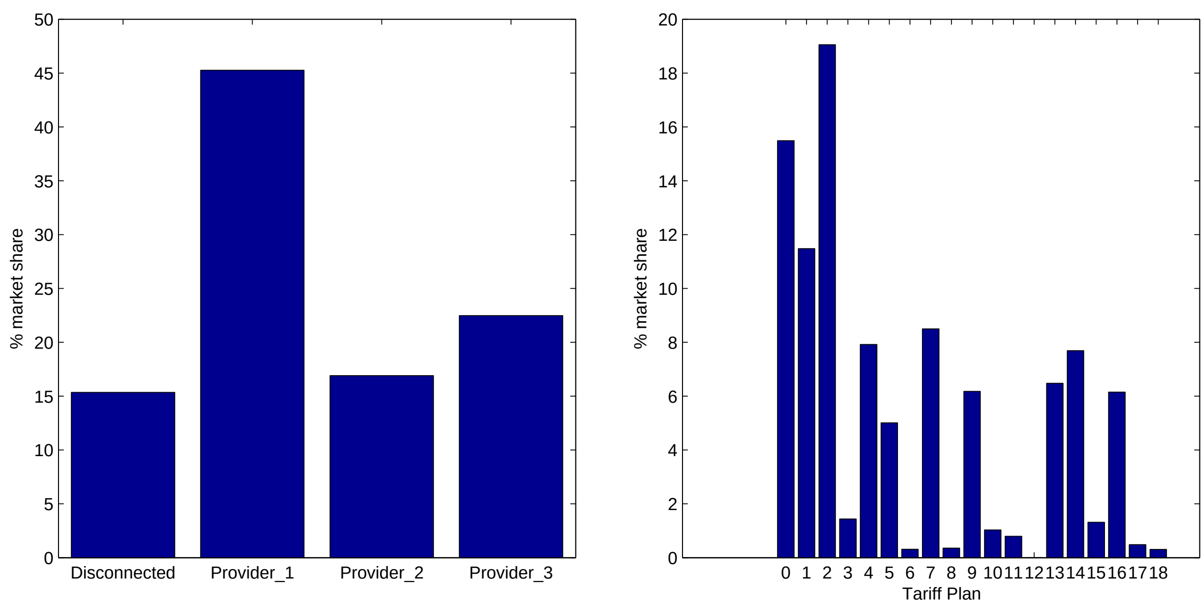
(a) (b)

Figure 5.3: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Uncertainty_50" scenario.



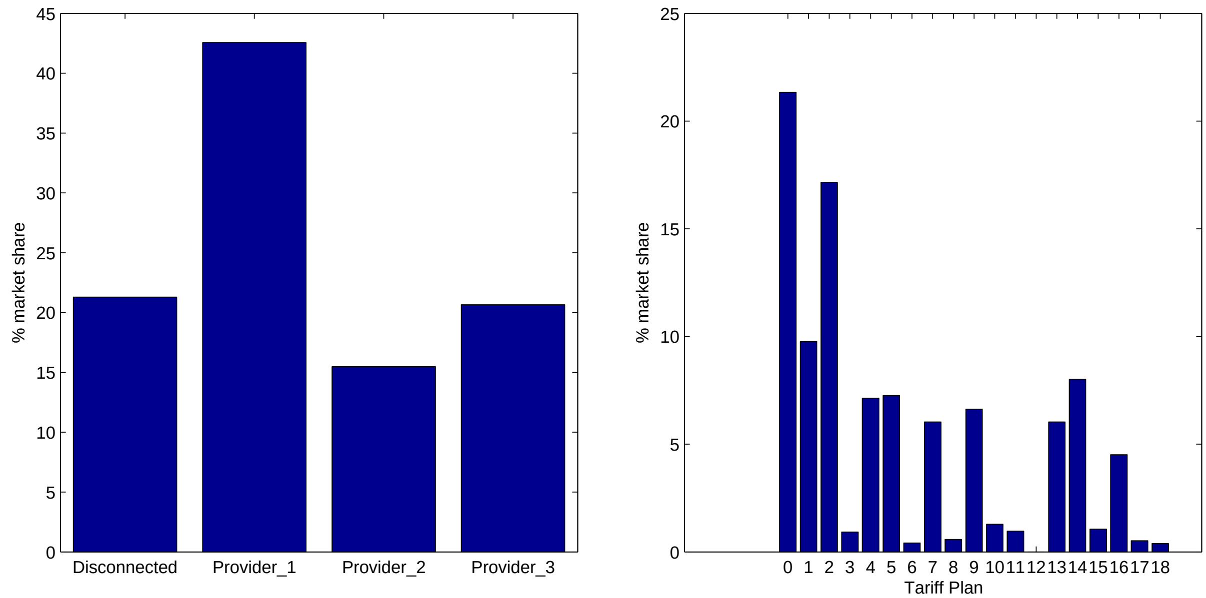
(a) (b)

Figure 5.4: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Uncertainty_100" scenario.



(a) (b)

Figure 5.5: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Uncertainty_200" scenario.



(a) (b)

Figure 5.6: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Uncertainty_300" scenario.

5.5.1 Users do not select the optimal tariff plan when they have uncertainty about their demand

Uncertainty in estimation of traffic demand leads users to select different tariff plans from that they would have selected if they have perfect knowledge of it. This is quite an expected result as users try to select the cost minimizing plan based on their traffic demand. When there is inaccuracy in their estimation, there is a high probability that they won't select the appropriate tariff plan. We depict this trend in Table 5.4, where the 2nd column provides the percentage of users selecting a different tariff plan from that they had selected in "Perfect Knowledge" scenario. Users that were active in "Perfect Knowledge" scenario, but became disconnected in uncertainty

Table 5.4: The impact of uncertainty on tariff plan selection

Scenario	% of Users Selecting "Wrong" Plan
Uncertainty_50	49.07%
Uncertainty_100	60.78%
Uncertainty_200	66.15%
Uncertainty_300	64.80%

scenarios are not taken into consideration. It might be expected, to a certain extend, that users won't be able to select the cost minimizing plan if they have inaccuracy in the estimation of their traffic demand. However, this percentage seems to be quite high, even with a low degree of uncertainty. We observe that almost one in two users selects a “wrong” tariff plan, while this percentage becomes much higher as uncertainty increases. A similar trend is mentioned in [40,41], where is noticed that almost half of the consumers do not select the cost minimizing plan, even if they had to choose only between three tariff plans.

Interestingly, we observe that $Tariff\_12$ is not selected by any user, in any of our simulation scenarios (including all cases of sensitivity analysis). This means that $Tariff\_12$ is always more expensive, compared to others, with any combination of traffic demand. However, this tariff plan existed in market, meaning that there were users who selected it. We can infer that in tariff plan selection, price is not the only factor affecting user choices. Other factors, like brand appeal, special offers (i.e., mobile devices), marketing, and subscriber confusion, may affect user choices. This fact may imply also that price obfuscation exists, intentionally or not, and easily could confuse users [62].

5.5.2 Uncertainty in traffic demand increases the number of disconnected users

We could imagine, to some extent, that inaccuracy in traffic demand will lead some users to overestimate their demand and abstain from the market, but at the same time there are users that underestimate it and participate in the market that normally they shouldn’t do. Table 5.5 provides the percentage of disconnected users in each scenario. Among users, there is a percentage

Table 5.5: The impact of uncertainty on disconnected users

Scenario	% of Disconnected Users
Perfect Knowledge	3.25%
Uncertainty_50	6.02%
Uncertainty_100	9.78%
Uncertainty_200	15.41%
Uncertainty_300	21.41%

that cannot afford to select a tariff plan to serve their demand, according their WtPay. These users will unavoidably abstain from the market and inaccuracy will hardly affect them. Some users that underestimate their demand probably will not change tariff plan, or they will select a cheaper one from that they would have selected in “Perfect Knowledge” scenario. These users will participate in the market. Users that overestimate their demand probably will have to pay more for a different tariff plan that satisfies them. A percentage of them might not have the WtPay for a more expensive plan, and subsequently will abstain from the market. This is the reason why disconnected users increase with uncertainty. We see on Table 5.5 that the higher the uncertainty, the more users abstain from the market. In “Uncertainty_300” scenario, more than one in 5 users prefer to remain disconnected rather than selecting a tariff plan.

5.5.3 Users spend more with uncertainty

This could be considered as a consequence of not selecting the cost minimizing plan. Inaccuracy in estimation of traffic demand leads users to select different tariff plans, thus paying more money to serve their demand. We can clearly see this trend in the following figure (Fig. 5.3), which provides the ECDF of money spent per user for tariff plan, in each scenario. Note that x-axis is in log-scale and disconnected users are excluded. We see that users pay less for a tariff plan in "Perfect

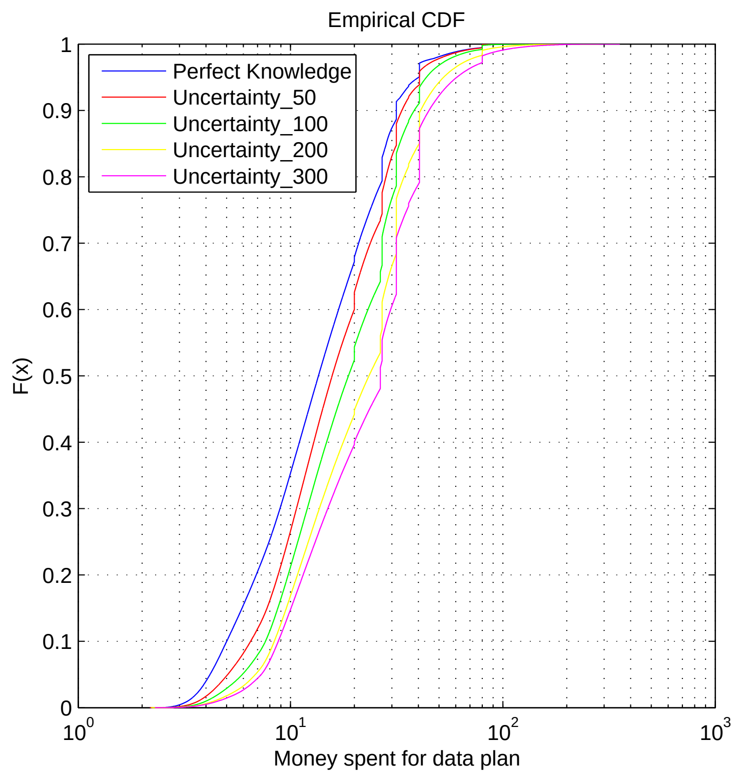


Figure 5.7: ECDF of money spent for tariff plan - all scenarios.

Knowledge" scenario, while as uncertainty increases the curve is shifted to the right, implying that users spend more when there is inaccuracy in traffic demand estimation. Mean cost, per user per month, is 16.38 Euros in "Perfect Knowledge" scenario and it increases to 18.96, 21.42, 24.97, and 27.56 Euros in scenarios "Uncertainty_50", "Uncertainty_100", "Uncertainty_200", and "Uncertainty_300", respectively.

5.5.4 Users may have negative benefit as uncertainty increases

As benefit is considered the amount of money saved when selecting a tariff plan. User's i benefit is measured as $p_i^{max} - p_{j,i}$, where p_i^{max} is user's i WtPay and $p_{j,i}$ the cost created for user i, from selecting the tariff plan j. Equivalently, it can be considered that a user would select the tariff plan that maximizes his welfare. Users who pay a bill close to their WtPay, obviously, are not as satisfied as those who pay a much lower amount. We evaluate the level of user satisfaction by analyzing money saved, per user, in each scenario. Fig. 5.8 presents users' benefit in all scenarios.

We observe that users have the maximum benefit when they know their actual demand, while

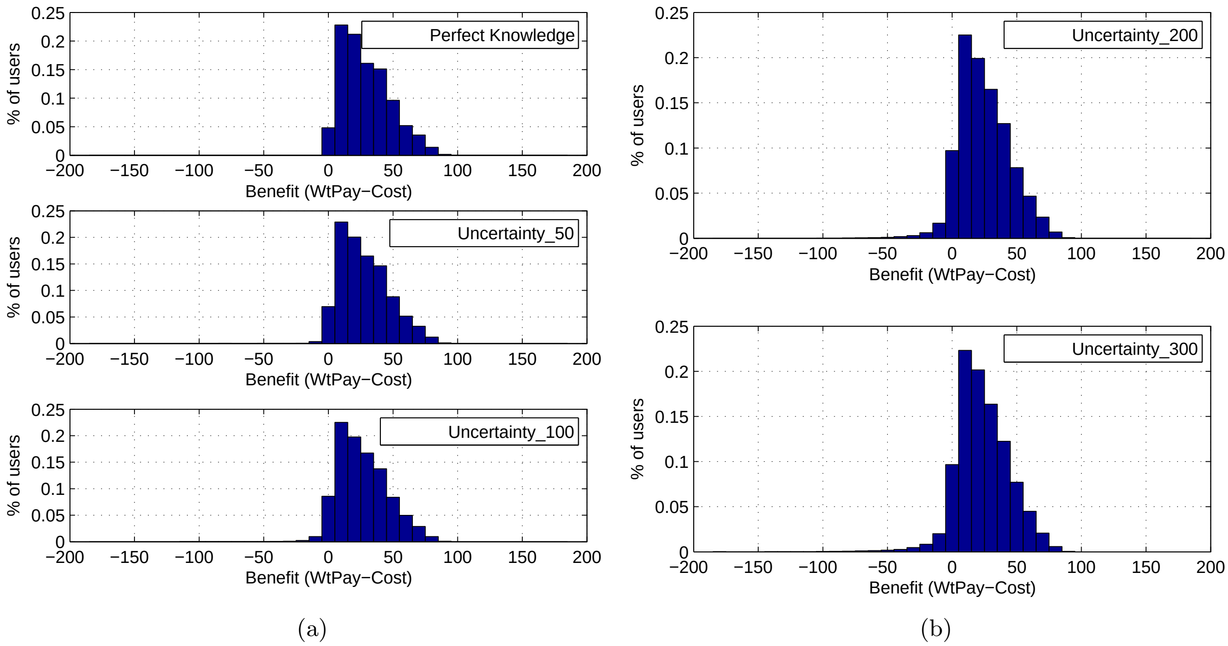


Figure 5.8: Users' benefit (in Euros/month).

the benefit is decreasing with uncertainty. Interestingly, we see that in all uncertainty scenarios there are users with negative benefit, i.e., they spent more for a tariff plan that they were willing to (more than their WtPay). This trend can be attributed to those who underestimate their traffic demand. Users who underestimate their demand may select a tariff plan, which assumed optimal based on their estimated usage. However, when they are charged, based on their actual usage, the money paid are much more than they expected, and for some users, may exceed the WtPay threshold. Only in "Perfect Knowledge" scenario there are no users suffering from negative benefit. Then, for a user to be able to control precisely his monthly bill and avoid bill shocks, the accurate estimation of his traffic demand is of high importance. U-plan could be a valuable tool, by informing users about their actual demand and facilitating them to select the optimal tariff plan. With the contribution of u-plan, users avoid to be charged over their WtPay and can control their monthly bill. It is not, therefore, an exaggeration to say that applications like u-plan are users powerful solutions to avoid bill shock, if operators are not obliged to inform them [64]. Mean benefit, per user per month, is 29.05 Euros in "Perfect Knowledge" scenario and it decreases to 27.91, 26.56, 24.54, and 23.39 Euros in scenarios "Uncertainty_50", "Uncertainty_100", "Uncertainty_200", and "Uncertainty_300", respectively. Disconnected users are not included in this study.

5.5.5 Operators' profit increases with uncertainty

Operators seem to be the entity that benefits from user uncertainty. As inaccuracy in traffic demand increases, they reap the extra amount of money spent by subscribers. Table 5.6 presents operators' revenue as percentage of the total wealth in the market, for each scenario. We could

Table 5.6: Operators' profit as percentage of total wealth

Scenario	Operators' Profit
Perfect Knowledge	35.92%
Uncertainty_50	39.06%
Uncertainty_100	42.35%
Uncertainty_200	46.30%
Uncertainty_300	47.48%

imagine that operators' profit should be increased with uncertainty, as this trend is also mentioned in [39, 40]. In our analysis, however, we take into account users that become disconnected as uncertainty increases. One could expect that operators' revenue could be negatively affected as more and more users abstain from the market. Although, we observe that operators reap the maximum profit in "Uncertainty_300", where the number of disconnected users is at its higher level (21.41%). It seems that the money paid from subscribers, in uncertainty scenarios, outweighs the losses from disconnected users.

5.6 Discussion on sensitivity analysis

An important question in this study, is how the characteristics of user population affect the performance of the market (i.e., money paid for tariff plan, percentage of disconnected users, and operators' profit). We consider several cases (Exponential Demand, More Low-WtPay Users, and Increased Demand) where we change, each time, specific characteristics of user population. We describe each case and present our results in the following subsections.

We expect that the use of a different distribution (e.g., exponential) for traffic demand modeling would not affect our main results. It will probably alter users' distribution among tariff plans, and operators subsequently, but we will observe the same trends as with lognormal traffic demand. This happens as each user will still have a specific demand and a specific WtPay to serve it. Inaccuracy in the estimation will lead users to not selecting the optimal plan, and consequently, more expenses for them and increased revenue for providers. Different distributions may assign different characteristics to a user population, however, the main trends of our study will still be observed.

We also expect that an increase in low-WtPay users in the market would lead to an increase in disconnected users and an increase in the number of users selecting tariff plans with low access fee, compared to the baseline case described in this chapter. As inaccuracy remains at low level, we do not expect to see significant differences, however, as inaccuracy increases, more and more users will abstain from the market. This happens, as the majority of users in the market have a low budget to support their demand. As inaccuracy increases, a percentage of users who overestimate their traffic demand cannot afford to buy a tariff plan to serve it and remain disconnected. This percentage will be higher than that of the baseline case. For those who underestimate their traffic demand and select a tariff plan, the money paid will exceed their WtPay, thus leading to high expenses. Probably, the percentage of users who suffer from negative benefit will be increased, compared to the baseline case. For that reason, we expect to see the profit gained by operators close to the profit gained in the baseline case.

Finally, an increase in traffic demand, keeping constant the WtPay, will result in an increase of disconnected users. This increase will be more intense as uncertainty increases. This is due to the total increase in traffic demand in the market. Users have increased needs in voice minutes, sms, and data, however, the available amount of money offered to serve this demand remains the same as in the baseline case. As an effect, a higher percentage of users is not able to buy a tariff plan, contributing to an increase of disconnected users. An inverse trend would be observed if we increase WtPay, while keeping constant the traffic demand. In this case, users offer a larger amount of money for tariff plan selection, in order to serve the same demand. Thence, the number of users that cannot afford to buy a plan is lower, compared to the baseline case, reducing further the number of disconnected users.

5.6.1 Exponential Demand

We remind market characteristics of the baseline case in Table 5.7.

Table 5.7: Market characteristics in baseline case

User Category	% of Population	WtPay (Euros)	Mean Monthly Traffic Demand		
			Data (MBs)	Voice (Minutes)	Sms
Low-WtPay	25%	10-25	25	55	10
Medium-WtPay	50%	25-60	75	140	30
High-WtPay	25%	60-100	200	350	80

In this case we use the exponential distribution to model the user demand for each service. Thence, for low-WtPay users we use the exponential distribution with $\lambda_{Data}^{-1} = 25$ MBs, $\lambda_{Voice}^{-1} = 55$ Minutes, and $\lambda_{Sms}^{-1} = 25$ Sms, for variables $Data$, $Voice$, and Sms, respectively. For medium-WtPay users an exponential distribution with $\lambda_{Data}^{-1} = 75$ MBs, $\lambda_{Voice}^{-1} = 140$ Minutes, and $\lambda_{Sms}^{-1} = 30$ Sms, and for high-WtPay users an exponential distribution with $\lambda_{Data}^{-1} = 200$ MBs, $\lambda_{Voice}^{-1} = 350$ Minutes, and $\lambda_{Sms}^{-1} = 80$ Sms. The following figures present users' distribution among operators and tariff plans for each scenario.

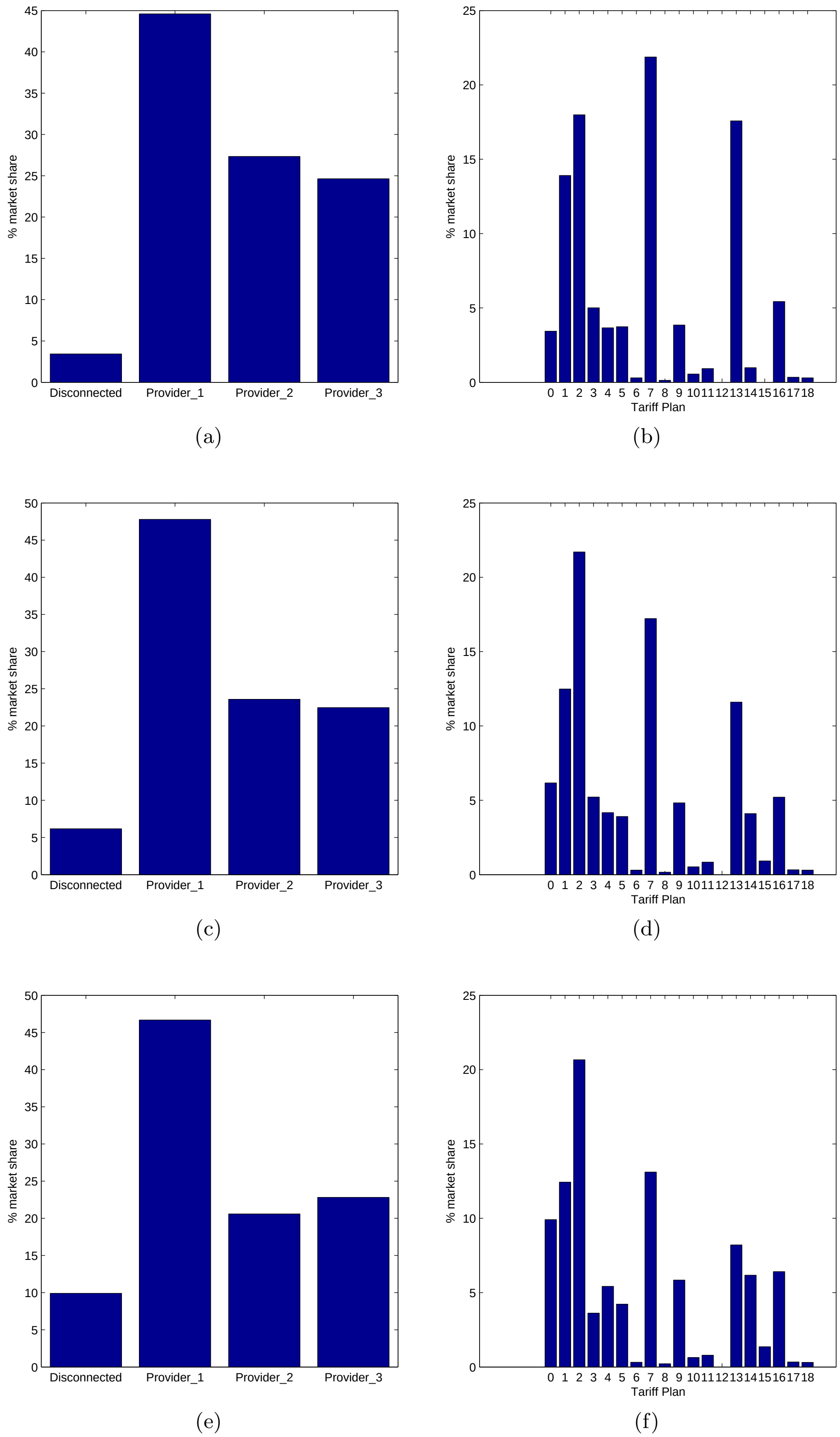


Figure 5.9: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Perfect Knowledge" scenario. (c) Users' distribution among operators and (d) Users' distribution among tariff plans in "Uncertainty_50" scenario. (e) Users' distribution among operators and (f) Users' distribution among tariff plans in "Uncertainty_100" scenario. Exponential Demand case.

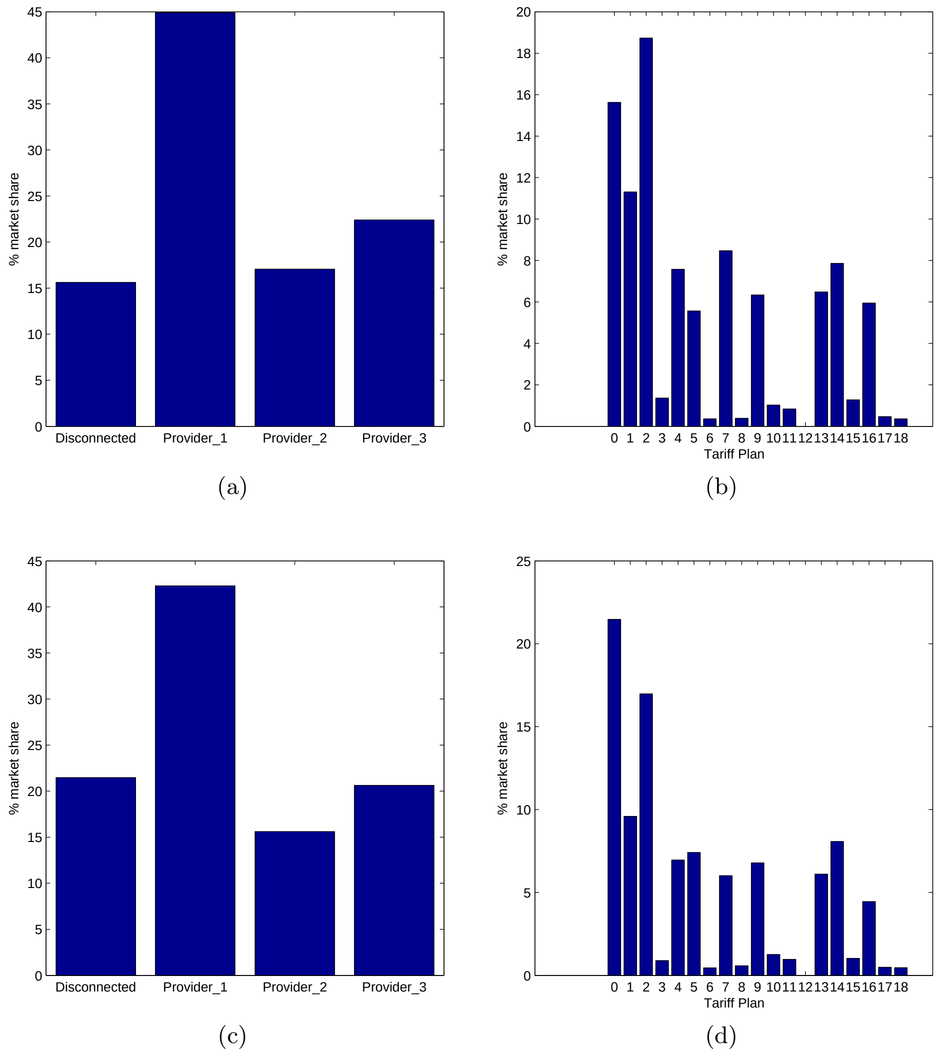


Figure 5.10: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Uncertainty_200" scenario. (c) Users' distribution among operators and (d) Users' distribution among tariff plans in "Uncertainty_300" scenario. Exponential Demand case.

Table 5.8 presents the results for the Exponential Demand case. Mean cost, per user per month, is 16.12 Euros in "Perfect Knowledge" scenario and it increases to 17.52, 19.07, 21.04, and 21.79 Euros in scenarios "Uncertainty_50", "Uncertainty_100", "Uncertainty_200", and "Uncertainty_300", respectively.

Table 5.8: Results for the Exponential Demand case

Scenario	% of Users Selecting "Wrong" Plan	% of Disconnected Users	Operators' Profit
Perfect Knowledge	-	3.43%	35.35%
Uncertainty_50	47.39%	6.16%	38.41%
Uncertainty_100	59.54%	9.91%	41.82%
Uncertainty_200	65.48%	15.62%	46.13%
Uncertainty_300	64.56%	21.47%	47.78%

5.6.2 More Low-WtPay Users

Here we consider the case where the majority of users in the market are low-WtPay users. The market we simulate in this case has the characteristics presented in Table 5.9. Traffic demand for each user category is modeled as in the baseline case, using a lognormal distribution, with the same parameters. Fig. 5.11 and Fig. 5.12 present users' distribution among operators and tariff plans for each scenario.

Table 5.9: Market characteristics in More Low-WtPay Users case

User Category	% of Population	WtPay (Euros)	Mean Monthly Traffic Demand		
			Data (MBs)	Voice (Minutes)	Sms
Low-WtPay	50%	10-25	25	55	10
Medium-WtPay	30%	25-60	75	140	30
High-WtPay	20%	60-100	200	350	80

Table 5.10 presents the results for the More Low-WtPay Users case. Mean cost, per user per month, is 13.45 Euros in "Perfect Knowledge" scenario and it increases to 14.66, 15.60, 16.65, and 16.90 Euros in scenarios "Uncertainty_50", "Uncertainty_100", "Uncertainty_200", and "Uncertainty_300", respectively.

Table 5.10: Results for the More Low-WtPay Users case

Scenario	% of Users Selecting "Wrong" Plan	% of Disconnected Users	Operators' Profit
Perfect Knowledge	-	3.65%	35.86%
Uncertainty_50	49.33%	8.80%	39.09%
Uncertainty_100	58.40%	15.26%	41.60%
Uncertainty_200	60.83%	23.08%	44.41%
Uncertainty_300	58.11%	29.91%	45.09%

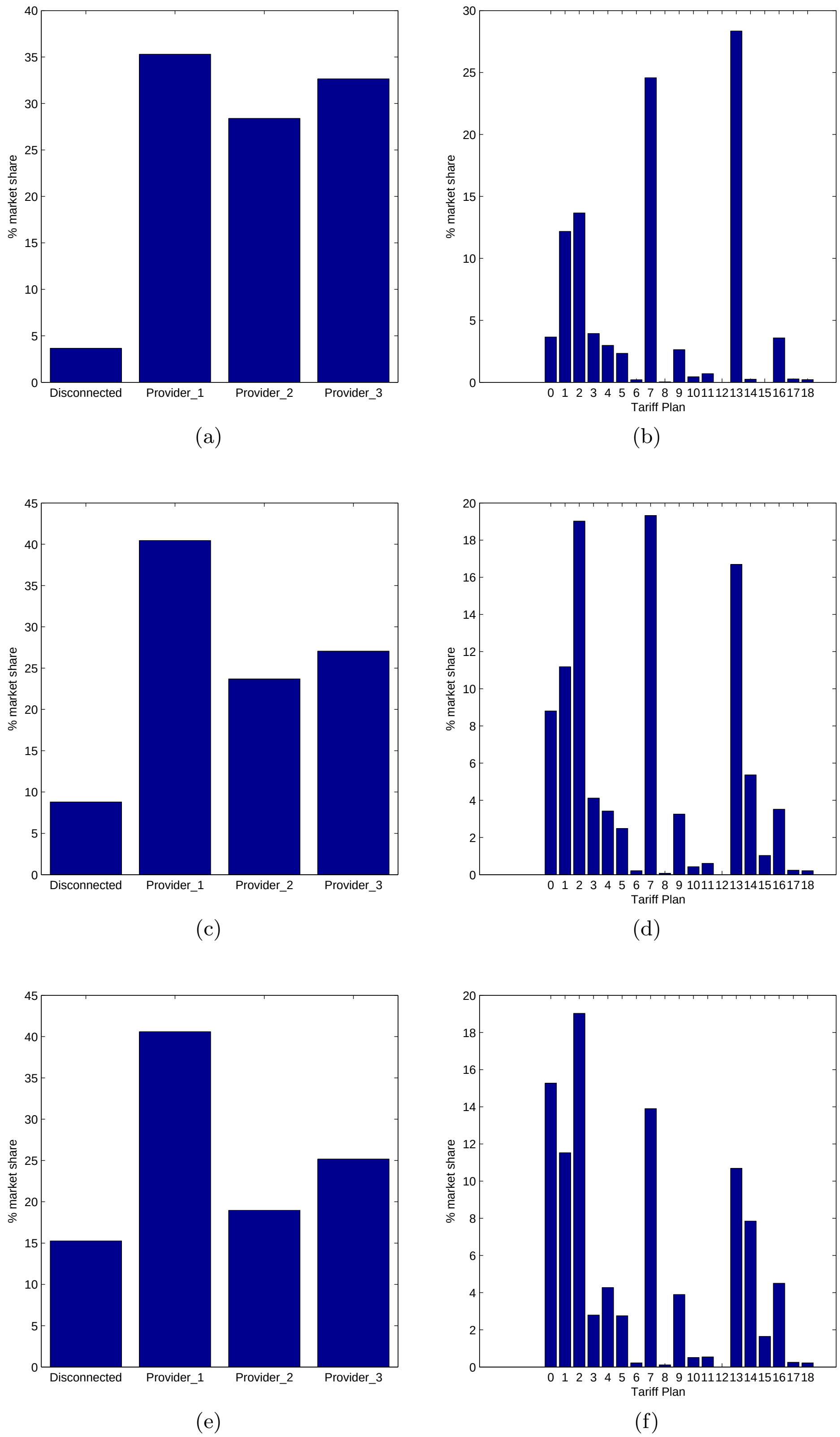


Figure 5.11: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Perfect Knowledge" scenario. (c) Users' distribution among operators and (d) Users' distribution among tariff plans in "Uncertainty_50" scenario. (e) Users' distribution among operators and (f) Users' distribution among tariff plans in "Uncertainty_100" scenario. More Low-WtPay Users case.

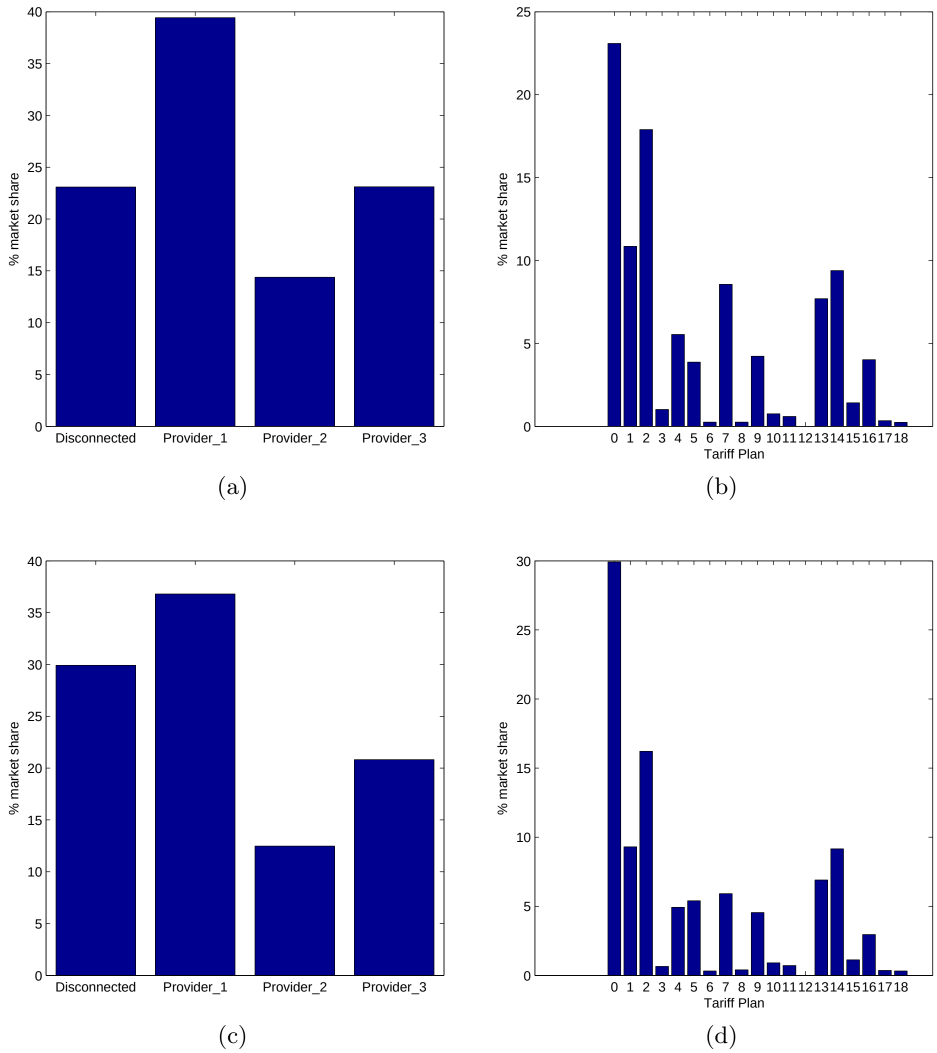


Figure 5.12: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Uncertainty_200" scenario. (c) Users' distribution among operators and (d) Users' distribution among tariff plans in "Uncertainty_300" scenario. More Low-WtPay Users.

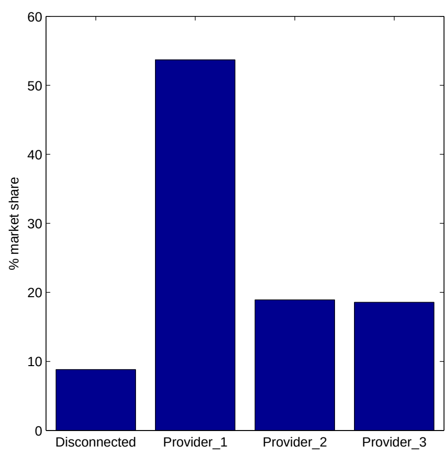
5.6.3 Increased Demand

In this case we simulate a market, where mean traffic demand for each service is by 50% increased for each user category, compared to the baseline case. The market we simulate in this case has the characteristics presented in Table 5.11. Traffic demand is modeled using a lognormal distribution, with mean values the values depicted in Table 5.11 and standard deviation slightly higher than the mean for each user category. The following figures present the results for each scenario.

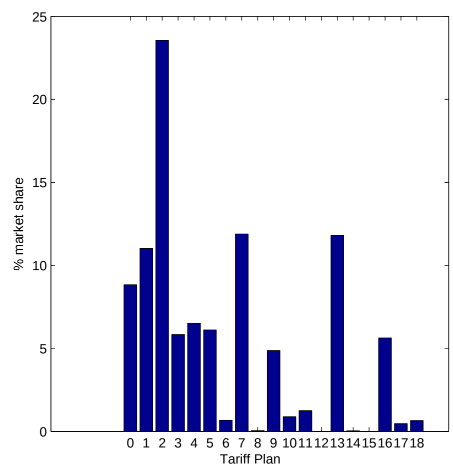
Table 5.12 presents the results for the Increased Demand case. Mean cost, per user per month, is 19.73 Euros in "Perfect Knowledge" scenario and it increases to 20.93, 22.36, 24.25, and 24.99 Euros in scenarios "Uncertainty_50", "Uncertainty_100", "Uncertainty_200", and "Uncertainty_300", respectively.

Table 5.11: Market characteristics in Increased Demand case

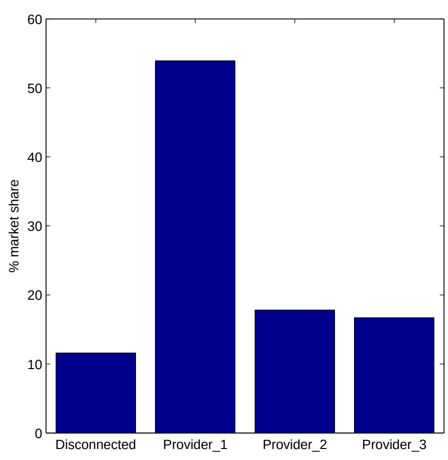
User Category	% of Population	WtPay (Euros)	Mean Monthly Traffic Demand		
			Data (MBs)	Voice (Minutes)	Sms
Low-WtPay	25%	10-25	37.5	82.5	15
Medium-WtPay	50%	25-60	112.5	210	45
High-WtPay	25%	60-100	300	525	120



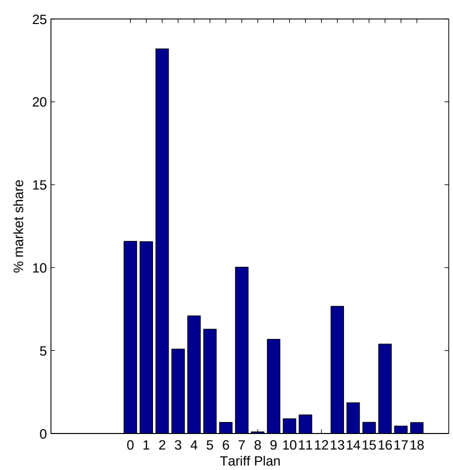
(a)



(b)



(c)



(d)

Figure 5.13: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Perfect Knowledge" scenario. (c) Users' distribution among operators and (d) Users' distribution among tariff plans in "Uncertainty_50" scenario. Increased Demand case.

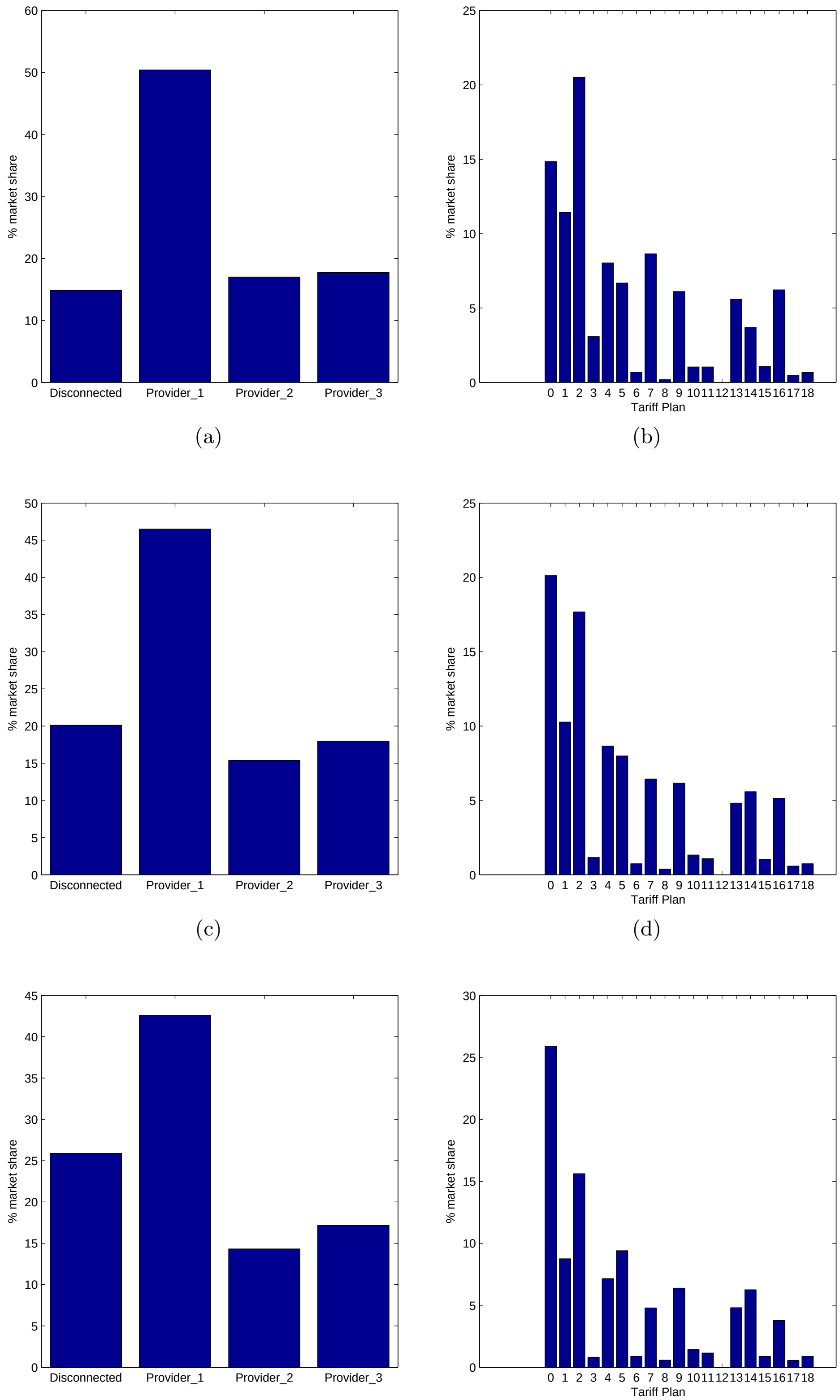


Figure 5.14: (a) Users' distribution among operators and (b) Users' distribution among tariff plans in "Uncertainty_100" scenario. (c) Users' distribution among operators and (d) Users' distribution among tariff plans in "Uncertainty_200" scenario. (e) Users' distribution among operators and (f) Users' distribution among tariff plans in "Uncertainty_300" scenario. Increased Demand case.

Table 5.12: Results for the Increased Demand case

Scenario	% of Users Selecting "Wrong" Plan	% of Disconnected Users	Operators' Profit
Perfect Knowledge	-	8.82%	43.26%
Uncertainty_50	43.04%	11.58%	45.88%
Uncertainty_100	54.25%	14.85%	49.03%
Uncertainty_200	59.87%	20.11%	53.16%
Uncertainty_300	59.08%	25.90%	54.79%

Chapter 6

Conclusions and Future Work

We studied a wireless access market, where an MVNO serves end-users in the retail market and a MNO provides access to the MVNO in the wholesale market. The pricing policies for both operators that maximize wealth share were found. In the absence of capacity constraints, the optimal pricing strategies for both operators depend only on the distribution of users' WtPay. The contribution of u-map in collecting information about user preferences and building user profiles has been highlighted. The impact of the availability of such information (e.g., traffic demand and WtPay) on the design of tariff plans was analyzed. We demonstrated that partial information may cause profit loss, but, due to the interaction between the operators, it is also possible to reap gain.

We also modeled a wireless access market where a user population, with specific traffic demand characteristics, tries to select the optimal (i.e., cost minimizing) plan to serve its demand. We assumed that each user is able to select the best plan, based on the estimation of his traffic demand, and evaluated the consequences of traffic demand uncertainty on user choices, expenses, and operators' profit. We have found that the uncertainty in traffic demand estimation leads to overspending and increased number of disconnected users, while it is also possible for some users to spend more than their WtPay, thus having negative benefit. For operators, user uncertainty seems beneficial, as users' increased expenses have direct, positive impact to their revenue.

The analysis can be extended as follows. It would be interesting to see how the prices evolve when there is competition in the retail market under the presence of more than one operators and, especially, when the MNO is also active in the retail market. It is also interesting to see how capacity constraints, on operators' network, affect the functionality of a wireless market. Finally, it would be important to model and analyze the trade-off of QoE vs. price and its impact on price setting, by considering cases where the larger the traffic of an operator, the poorer the QoE.

Modeling the user behavior under three part tariffs is also of high importance. An extension of this study could be the incorporation, apart from the price, of the QoS, perceived value of content, and brand appeal perception. From operators' perspective, an important issue is the churn prevention and the type of criteria that influence user choices on tariff plans. Moreover, a related issue is the design of beneficial tariff plans. Finally, an interesting aspect is how the knowledge collected from u-map and social networking applications can be exploited for user categorization and tariff plan design, by extension.

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