

Economics of WiFi Offloading: Trading Delay for Cellular Capacity

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Abstract—Cellular networks are facing severe traffic overloads due to the proliferation of smart handheld devices and traffic-hungry applications. A cost-effective and practical solution is to offload cellular data through WiFi. Recent theoretical and experimental studies show that a scheme, referred to as delayed WiFi offloading, can significantly save the cellular capacity by delaying users' data and exploiting mobility and thus increasing chance of meeting WiFi APs (Access Points). Despite a huge potential of WiFi offloading in alleviating mobile data explosion, its success largely depends on the economic incentives provided to users and operators to deploy and use delayed offloading. In this paper, we study how much economic benefits can be generated due to delayed WiFi offloading, by modeling the interaction between a single provider and users based on a two-stage sequential game. We first analytically prove that WiFi offloading is economically beneficial for both the provider and users. Also, we conduct trace-driven numerical analysis to quantify the practical gain, where the increase ranges from 21% to 152% in the providers revenue, and from 73% to 319% in the users surplus.

Index Terms—WiFi offloading, delayed offloading, economic analysis, stackelberg game, pricing.

I. INTRODUCTION

MOBILE data traffic is growing enormously, as smart phones/pads equipped with high computing powers and diverse applications become popular. Cisco reported that global mobile data traffic grew 2.3-fold in 2011, more than doubling for the four consecutive years since 2008 [1]. It was also forecast there that the total global mobile data traffic will increase 18-fold between 2011 and 2016, where the average smartphone is projected to generate 1.3 GB per month in 2015 [1]. To cope with mobile data explosion, upgrading to 4G (e.g., LTE (Long Term Evolution) or WiMax), may be an immediate solution, but mobile applications are becoming more diverse with larger data consumption and the number of smartphone/pad users are also increasing rapidly. Then, users' traffic demand is expected to exceed the capacity of 4G in the

near future, and thus cellular operators¹ keep seeking other alternatives to efficiently respond to data explosion [2], [3].

WiFi offloading, where users use WiFi prior to 3G whenever they have data to transmit/receive, has been receiving a lot of interest as a practical solution that can be applied without much financial burden in practice. Network operators as well as users can easily and quickly install WiFi access points (APs) with low costs, and in fact many operators worldwide have already provided WiFi services in hot-spots and residential areas. Recent papers [4], [5] demonstrate that a huge portion of cellular traffic can be offloaded to WiFi by letting users delay their delay-tolerant data (e.g., movie, software downloads, cloud backup and sync services), and upload/download data whenever they meet a WiFi AP within a pre-specified delay deadline. We call this *delayed WiFi offloading*, and about 60-80% of cellular traffic can be reduced when 30 mins to 1 hour delay for human mobility [4] and 10 mins of delay for vehicular mobility [5] are allowed. This remarkable offloading efficiency is due to users' mobility enabling themselves to be under a WiFi coverage during a considerable portion of their business time. Example usage scenarios include: 1) Alice records video of a family outing at a park using her cell phone and wants to archive it in her data storage in the Internet. She does not need the video immediately until she comes back home in several hours. 2) Bob will travel this afternoon from New York to Los Angeles and he just realizes that he can use some entertainment during the long flight. As he has several hours before the trip, he schedules to download a couple of movies on his cell phones.

However, WiFi offloading's high potential does not always guarantee that users and providers actually adopt it in practice. First, users may be reluctant to delay their traffic without economic incentives, e.g., discounted service fees. For example, if a user pays based on an unlimited data plan, users may have no reason to delay traffic unless WiFi-required services, e.g., services requiring higher bandwidths, are necessary. Also, operators may not always welcome delayed offloading service, since the total cellular traffic to charge may decrease, possibly leading to its revenue reduction. Thus, it is of significant importance to formally address the question on the economic gains of delayed WiFi offloading from the perspective of users, operators, and regulators, which is the focus of this paper.

In this paper, we consider the interaction between a single provider and users based on a two-stage sequential game, where the operator controls the price and users are price-takers. A variety of control knobs will show different eco-

¹We use 'operator' and 'provider' interchangeably throughout this paper.

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conomic impacts of delayed WiFi offloading. Our major focus is to understand how and how much users and the provider obtain the economic incentives by adopting delayed WiFi offloading and investigate the effect of different pricing and delay-tolerance. The major features of our model include four different pricing schemes (flat, volume, two-tier, and congestion) and heterogeneous users in terms of traffic demands and willingness to pay.

Using the market model mentioned above, we first conduct analytical studies under flat and volume pricing for the simple cases when the traffic demand follows a certain distribution (obtained from known measurement studies), and users are uniformly distributed among cells. This simplification seems to be unavoidable for mathematical tractability, yet it helps to fundamentally understand how the users and the provider become economically beneficial. We formally prove that delayed WiFi offloading indeed generates the economic incentives for the users and the provider. To obtain more practical messages and quantify the gain of delayed WiFi offloading, we use two traces, each of which tells us the information on cellular data usage and WiFi connectivity. We extract the parameters needed by our model from those traces, and obtain numerical results, from which, we draw the following key messages:

- WiFi offloading is economically beneficial for both the provider and users, where depending on the pricing schemes and delay tolerance, the increase ranges from 21% to 152% in the provider's revenue and from 73% to 319% in the users' surplus.
- Revenue in volume pricing exceeds that in flat pricing. However, the revenue *increasing rate* of delayed offloading in flat pricing is higher than that in volume pricing.
- Pricing with higher granularity such as two-tier and congestion pricing increases the revenue, compared to flat and volume pricing, but the gains become smaller as offloading efficiency increases (i.e., as users delay more traffic).
- The revenue gain from on-the-spot to delayed offloading is similar to that generated by the network upgrade from 3G to 4G.

II. RELATED WORK

There have been several works [4]–[6] on delayed WiFi offloading. Lee *et al.* [4] proposed a delayed offloading framework, where users specify a deadline for each application or data, and each delay tolerant data is served in a shortest remaining time first (SRTF) manner through WiFi networks. If the delay deadline of the data expires, then the data is transmitted through 3G networks. On real human mobility traces, it is shown that 80% of cellular traffic can be offloaded to WiFi networks when 1 hour delay is allowed. Balasubramanian *et al.* [5] proposed an offloading framework for vehicular networks, which supports fast switching between 3G and WiFi, and avoids bursty WiFi losses. They demonstrated that more than 50% of cellular traffic can be reduced for a delay tolerance of 100 seconds on vehicular mobility. Hultell *et al.* [6] addressed the user experienced performance of delayed transmission and proposed context-aware caching/prefetching to provide users immediate services, e.g. web browsing, news, and streaming. They found that more than 80% of news can be pre-fetched within 700 seconds, with only 50 WiFi APs per

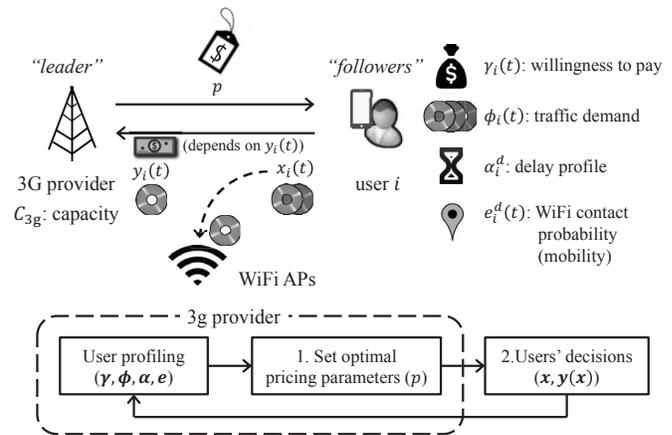


Fig. 1. An illustration of the system model. $x_i(t)$ and $y_i(t)$ are 3G+WiFi and 3G traffic volumes of user i at time t .

km² (1.2% spatial coverage) on a random mobility model. Therefore, WiFi networks are proven to offload large fraction of cellular data for various mobility conditions and low AP density, whenever data can tolerate some amount of delay.

Some recent works [7]–[9] devised incentive frameworks for users to delay their data traffic. Ha *et al.* [7] proposed a time-dependent pricing scheme for mobile data, which incentivizes users to delay their traffic from the higher- to lower-price time zone. They conducted surveys which revealed that users are indeed willing to wait 5 minutes (for YouTube videos) to 48 hours (for software updates). They addressed that the time-dependent pricing flattens temporal fluctuation of traffic usage and benefits wireless operators. In [8], [9], Zhuo *et al.* proposed an incentive framework for downlink mobile traffic offloading based on an auction mechanism, where users send bids, which include the delay it can tolerate and the discount the user wants to obtain for that delay, and a single provider buys the delay tolerance from the users. However, previous studies did not provide how much economic gain the provider and users can obtain. In this paper, we quantify the economic gain of delayed offloading based on real-world traces.

Gao *et al.* [10] investigated the economics of mobile data offloading through third-party WiFi or femtocell APs. They considered a market-based offloading solution, where base stations (BSs) pay APs for offloading traffic. While they studied the economic interaction between mobile network operators and APs as a non-cooperative game, we focus on the economic interaction between mobile network operators and subscribers, in this paper.

III. MODEL

We summarize the system model in Fig. 1. We model users with four attributes, (i) how much money they can pay (*willingness to pay*, γ), (ii) how much data they want to use (*traffic demand*, ϕ), (iii) how delay-tolerant each user is (*delay profile*, α), and (iv) how they move (*WiFi contact probability*, e). We index users by i , time slots by t , and deadlines by d . Assuming that the single provider knows users' attributes and strategies a priori, we model a market model based on a two-stage sequential game (e.g. Stackelberg game). At the first stage, the provider decides on the pricing parameters (p)

TABLE I
SUMMARY OF MAJOR NOTATION

Variable	Definition
N and C_{3g}	Number of users and Capacity of a BS cell
θ	Price sensitivity
$e_i^d(t)$	The WiFi contact probability of user i at slot t within deadline d
α_i^d	Portion of traffic of user i with deadline d
$x_i(t)$	3G+WiFi traffic volume of user i at slot t
$y_i(t)$	3G traffic volume of user i at slot t
$\phi_i(t)$	Traffic demand of user i at slot t
$w_i(t)$	Temporal preference (weight) of user i at time t
$\gamma_i(t)$	Willingness to pay of user i for traffic at time t

(for a fixed pricing scheme, which we will describe later) as a *leader*, and at the second stage, each user is a price-taker as a *follower* and chooses the 3G+WiFi traffic volume \mathbf{x} . Our analysis and numerical results are carried out based on the equilibrium of this game. We describe the detailed network, traffic, and market models in the following subsections.

A. Network and Traffic Model

1) *Network model*: We consider a network consisting of cellular base stations (BSs) and WiFi APs, where N users are served by the cellular provider.² Users are always guaranteed to be under the coverage of a cellular BS, but not necessarily of a WiFi AP. We consider a one-day time scale whose average analysis over the unit billing cycle, e.g., one month, is presented. A day is divided into time slots $t \in \{1, 2, \dots, T\}$, where T is the last index of one day, depending on the duration of a time slot.³ Let C_{3g} be the capacity (in volume per slot) provided by a BS.⁴

During each day, users move among BSs as well as APs. Let $e_i^d(t)$ be the probability that user i meets any WiFi AP within deadline d at time slot t . For instance, $e_i^{\text{1hour}}(13:00) = 0.7$ means that user i meets a WiFi AP from 1 p.m. to 2 p.m. with probability 0.7. The value of $e_i^d(t)$ can be obtained by analyzing user i 's mobility trace during, say, a month. We assume that only 3G traffic is charged. Each user has its own set of accessible, free WiFi APs, e.g., ones in home, office, or hotspots, deployed by users, users' companies, providers, or governments. We ignore the cost from offloaded data since the cost of accessing the Internet via a WiFi AP connected to a wired network is considerably lower than that for accessing the cellular network [11], [12]. According to [12], the per-bit TCO (total cost of ownership) of WiFi networks are 10% of the per-bit TCO of 3G networks. If there are many WiFi APs with poor connection, we may need to apply a threshold policy (e.g., applying WiFi offloading only when the data rate of WiFi is greater than 2Mbps) for rate-sensitive applications, where users do not offload to WiFi networks with poor connection (i.e., whose data rates are lower than a threshold). The WiFi contact probability, $e_i^d(t)$, will be changed accordingly.

2) *Traffic model*: We assume that user i has the average daily traffic demand Φ_i , 3G+WiFi traffic vector $\mathbf{x}_i = (x_i(t) : t \in T)$, and 3G traffic vector $\mathbf{y}_i(\mathbf{x}_i) = (y_i(t) : t \in T)$, where $x_i(t)$ is the traffic volume of user i at slot t , transferred through

either 3G or WiFi, and $y_i(t)$ is the traffic volume transferred through only 3G. The daily traffic demand Φ_i is temporally split into $\phi_i = (\phi_i(t) : t \in T)$, where $\phi_i(t)$ is traffic demand at slot t , and $\Phi_i = \sum_{t \in T} \phi_i(t)$. The traffic volume of user i at slot t is constrained by the traffic demand, i.e., $x_i(t) \leq \phi_i(t)$. We denote $w_i(t) = \frac{\phi_i(t)}{\Phi_i}$ as temporal preference (weight) of user i . For example, for a user i 's traffic demand 1 GB, where users want to send 700 MB at daytime and 300 MB at nighttime (i.e., just two time slots), $\phi_i(\text{day}) = 700$ and $\phi_i(\text{night}) = 300$, and $w_i(\text{day}) = 0.7$ and $w_i(\text{night}) = 0.3$. Users may not be able to deliver all traffic demand, and the actual transmitted volume depends on the price and user utility, which we will describe later. The traffic volume for 3G, \mathbf{y}_i which is actually charged, relies on \mathbf{x}_i as well as each user i 's WiFi contact probability (mobility) and delay profile, which we define in the following paragraph.

We introduce a notion of *delay profile* to model per-user delay-tolerance of traffic. The delay profile is denoted by $\boldsymbol{\alpha} = (\alpha_i^d : i \in N, d \in \{0, 1, \dots, D\})$ such that $\sum_{d=0}^D \alpha_i^d = 1$, where α_i^d is the portion of user i 's traffic that allows deadline d , and D is the maximum allowable deadline across all traffic. For example, for a user i 's traffic demand 1 GB, if the user has 300 MB, 700 MB, allowing 10 mins and 1 hour, resp., we have $\alpha_i^{10m} = 0.3$, $\alpha_i^{1h} = 0.7$. For a given per-user delay profile, each user uses only WiFi connections to deliver some data until the allowable deadline expires, after which the remaining data is immediately transferred through 3G. In particular, when no delay is allowed ($\alpha_i^0 = 1$), we call this regime *on-the-spot* offloading, where a user only uses spontaneous connectivity of WiFi. Most current smartphones support this by default.

B. Market Model

We start by explaining the economic metrics of the users and the provider. We assume that the provider and users are rational and try to maximize revenue and utility.

1) *Users and Provider*: We model heterogeneous willingness to pay among users over time slots, which we denote by $\gamma_i(t) \geq 0$ for user i at time t . For an average user i , $\gamma_i(t)$ tends to be higher when t is in daytime. We first define user i 's utility at time slot t by $\gamma_i(t)x_i(t)^\theta$, where the constant $\theta \in (0, 1)$ is price-sensitivity. The utility function $\gamma_i(t)x_i(t)^\theta$ is called an *iso-elastic* function⁵ with the property of an increasing function of traffic volume $x_i(t)$ for all i and t , but of a decreasing marginal payoff. The *iso-elastic* function for data traffic is widely used in network economics to represent users' utility [13]–[17]. Then, user i 's (aggregate) net-utility $U_i(\mathbf{x}_i)$ during a day is:

$$U_i(\mathbf{x}_i) = \sum_{t \in T} \gamma_i(t)x_i(t)^\theta - m(p, \mathbf{y}_i(\mathbf{x}_i)),$$

where $m(p, \mathbf{y}_i(\mathbf{x}_i))$ is the daily payment charged by the provider whose price is p . We abuse the notation and use p to refer to the whole parameters of a given pricing scheme, and the function form of m differs across pricing schemes (see Section III-B2). Recall the notation $\mathbf{y}_i(\mathbf{x}_i)$ represents the dependency of the 3G traffic on 3G+WiFi traffic.

Given the traffic demand ϕ_i , WiFi contact probabilities $e_i^d(t)$, willingness to pay $\gamma_i = (\gamma_i(t) : t \in T)$, delay profile

²Throughout this paper, we use the words 'BS' and 'AP' to refer to a cellular BS and an WiFi AP, respectively.

³We also use N and T to refer to a set of all users and time slots to abuse the notation.

⁴We use '3G' to refer to a cellular network (e.g., W-CDMA, LTE).

⁵A function $u(x)$ is said to be *iso-elastic* if for all $k > 0$, $u(kx) = f(k)u(x) + g(k)$ for some functions $f(k), g(k) > 0$.

α_i^d , and a pricing scheme (and its parameters), each user i chooses \mathbf{x}_i^* to maximize his/her net-utility,

$$\text{User : } \max_{x_i(t) \leq \phi_i(t), \forall t \in T} U_i(\mathbf{x}_i), \quad (1)$$

where each user i subscribes to 3G service only if the net-utility is positive, i.e., $U_i(\mathbf{x}_i) > 0$.

Under a given pricing scheme, the provider decides on the price (more precisely, the parameters of the pricing scheme) to maximize its expected revenue, $R(p)$:

$$\text{Provider : } \max_{p \in \mathcal{P}} R(p), \quad (2)$$

where \mathcal{P} is the set of all feasible prices such that (i) the revenue is positive (*provider rationality*), and (ii) the expected 3G traffic volume at each time and at each BS cell is smaller than 3G capacity C_{3g} (*capacity constraint*).

The expected revenue $R(p)$ is the total *income* minus *cost*,

$$R(p) = \sum_{i \in N} m(p, \mathbf{y}_i(\mathbf{x}_i)) - \sum_{i \in N} c(\mathbf{y}_i(\mathbf{x}_i)), \quad (3)$$

where $c(\mathbf{y}_i)$ is the network cost to handle the 3G traffic, which we model by a linearly increasing function, $c(\mathbf{y}_i) = \eta \sum_{t \in T} y_i(t)$, where η is the cost of the unit volume of the 3G traffic. The cost term captures the money for operation and maintenance including electric power costs as well as customer complaints due to congestion. The linearly increasing network cost is commonly used in the analysis of cellular cost [18]. User surplus S is the summation of users' net-utility and social welfare W is the summation of user surplus and provider revenue, or,

$$S = \sum_{i \in N} U_i(\mathbf{x}_i),$$

$$W = \sum_{i \in N, t \in T} \gamma_i(t) x_i(t)^\theta - \sum_{i \in N} c(\mathbf{y}_i(\mathbf{x}_i)).$$

2) *Pricing*: For a given pricing scheme, the 3G provider fixes a *price parameter* which is announced to the users. We consider four pricing schemes - *flat*, *two-tier*, *volume*, and *congestion* - that are popularly studied in literature: Each pricing scheme has tunable parameters controlled by the provider: $\{p_f\}$, $\{p_t^1, p_t^2, y_{\max}^1\}$, $\{p_v\}$, and $\{p_v(t, s)\}$, which we elaborate shortly. For a given pricing scheme and its price parameters p , a user with 3G traffic volume \mathbf{y}_i pays $m(p, \mathbf{y}_i)$ to the provider. Note that if a user does not subscribe or generate any traffic, the payment is zero, i.e., $m(p, \mathbf{0}) = 0$.

Flat. The provider offers unlimited service for users who pay a subscription fee p_f .

Two-tier. Multiple price points are provided for several usage options. For example, AT&T has a pricing plan that offers up to 200 MB, 2 GB, and 4 GB for \$15, \$25, and \$45 per month, respectively. In this paper, we consider two price points, where the provider offers maximum daily traffic volume y_{\max}^1 for fixed fee p_t^1 and unlimited service for fixed fee p_t^2 , or,

$$m(p, \mathbf{y}_i) = \begin{cases} p_t^1, & \text{if } 0 < \sum_{t \in T} y_i(t) \leq y_{\max}^1. \\ p_t^2, & \text{if } \sum_{t \in T} y_i(t) > y_{\max}^1. \end{cases}$$

Volume. A user is charged to pay p_v for the unit 3G traffic volume, or,

$$m(p, \mathbf{y}_i) = p_v \cdot \sum_{t \in T} y_i(t).$$

Congestion. We consider a volume-based congestion pricing, or simply congestion pricing in this paper, where the price for a unit file size varies with time and location, or,

$$m(p, \mathbf{y}_i) = \sum_{t \in T} p_v(t, s_i(t)) \cdot y_i(t),$$

where $p_v(t, s)$ is the unit price at time slot t and cell s , and $s_i(t)$ is the cell identifier with which user i is associated at t .

We note that in flat and two-tier pricing, users do not subscribe to the service when the net-utilities are not positive, which is the major factor determining the provider's revenue, whereas in volume and congestion pricing, every user subscribes and just controls its traffic volume. Two-tier and congestion pricing schemes are the extensions of flat (in terms of price granularity) and volume (in terms of space and time), resp. Tiered pricing in mobile data services is popularly used recently [1] as the provider can set up multiple pricing points, while maintaining simplicity in the pricing structure. Congestion pricing has been considered as a way of revenue increase in networking services (see e.g., [7], [19], [20]). In fact, in the usage of cellular networks, it has been reported that spatial and temporal variation of mobile data traffic are shown to be remarkable [21], implying high potential in the increase of the provider's revenue and better resource utilization. Despite the high billing complexity, it is interesting to see its quantified impact in WiFi offloading.

IV. ANALYSIS OF WIFI OFFLOADING MARKET

In Sections IV-B and IV-C, we provide analytical studies of the economic gain of WiFi offloading. Due to complex interplays among pricing parameters, and more importantly users' heterogeneity, our analysis is made under several assumptions. This simplification seems unavoidable for mathematical tractability, yet it helps to understand how the users and the provider become economically beneficial. In Section V, we quantify economic gains of WiFi offloading in more practical settings (heterogeneous cells and willingness to pay of users) as well as complex pricing schemes (*two-tier* and *congestion*).

A. Assumptions and Definitions

A1. Homogeneous cells. User associations are uniformly distributed among cells so that it suffices to consider only a single BS cell, where the number of users is $\hat{N} = N/(\# \text{ of cells})$. The distribution of users' traffic demand in each cell is identical.

A2. Traffic demand distribution. In each cell, the daily traffic demand Φ_i follows a random variable Φ which follows an upper-truncated power-law distribution, given by: $f_\Phi(x) = x^{-\sigma}/Z$, for $0 \leq x \leq \Phi_{\max}$, where σ is the exponent, Φ_{\max} is the maximum value of Φ , and $Z = \frac{\Phi_{\max}^{1-\sigma}}{1-\sigma}$ with $0 < \sigma < 1$.

A3. Willingness to pay and temporal preference. Users are homogeneous in willingness to pay and temporal preference, i.e., $\gamma_i(t) = \gamma(t)$, $w_i(t) = w(t)$, $\forall i \in N$, $t \in T$. In regard to willingness to pay, we let $\gamma(t) = w(t)^{1-\theta}$. However user's traffic demand is heterogeneous as in **A2**.

A4. Pricing. We consider only flat and volume pricing. Thus, throughout this section, the pricing parameter p refers to the flat fee p_f and the unit price p_v in each pricing, resp.

In **A2**, we comment that in recent measurement studies [21], [22], the traffic volume distribution of cellular devices is shown to follow an upper-truncated power-law distribution. Especially, in [21], the adopted pricing policy was flat pricing, so that the measured traffic usage was not affected by pricing. Thus, we apply an upper-truncated power-law distribution to daily traffic demand Φ . In **A3**, willingness to pay $\gamma(t)$ at time t is set, such that at each time slot t (i) one has larger willingness to pay for larger traffic demand and (ii) utility generated by traffic demand ($\gamma(t)\phi(t)^\theta$) is proportional to the traffic demand ($\phi(t) = w(t)\Phi$). The exponent $1 - \theta$ is chosen to satisfy the condition (ii), where utility of a user with demand ϕ is $\gamma(t)\phi(t)^\theta = w(t)^{1-\theta}(w(t)\Phi)^\theta = w(t)\Phi^\theta$. The rationale behind the condition (ii) is that the expected monetary value of every bit of a user is equal across time slots (and $\gamma(t)x(t)^\theta$ is proportional to $x(t)$, if $x(t)$ is proportional to $\phi(t)$), but the value of bit differs by its application type.

Remark 4.1: User heterogeneity only comes from traffic demand Φ from our assumptions. For notational simplicity, we omit user subscript i and use subscript Φ to represent the user variables with traffic demand Φ , e.g., $x_\Phi(t)$, $y_\Phi(t)$, etc.

Offloading indicators. We first introduce two indicators to quantify how much 3G data is offloaded: (i) aggregate 3G traffic ratio κ_{avg} and (ii) peak 3G traffic ratio κ_{peak} .

Definition 4.1 (offloading indicators):

$$\kappa_{\text{avg}} \triangleq \frac{\sum_{t \in T} Y(t)}{\sum_{t \in T} X(t)}, \quad \kappa_{\text{peak}} \triangleq \frac{\max_{t \in T} Y(t)}{\sum_{t \in T} X(t)}, \quad (4)$$

where the transmitted total traffic and 3G traffic over a cell at time t , $X(t)$ and $Y(t)$ ⁶ are:

$$\begin{aligned} X(t) &= \hat{N} \int_0^{\Phi_{\text{max}}} x_\Phi(t) dF_\Phi, \\ Y(t) &= \hat{N} \int_0^{\Phi_{\text{max}}} \sum_{d=0}^D b_\Phi^d(t-d) x_\Phi(t-d) dF_\Phi, \end{aligned} \quad (5)$$

and $b_\Phi^d(t) = \alpha_\Phi^d(1 - e_\Phi^d(t))$ is the portion of the traffic generated at time t which is transmitted through 3G at time $t + d$.

It is clear that as users delay more traffic, the aggregate 3G traffic ratio κ_{avg} provably decreases, since more traffic can be offloaded through WiFi. Also, the peak 3G ratio κ_{peak} decreases as more traffic at *peak* time is offloaded. In Section V, we show that both κ_{avg} and κ_{peak} decrease as delay tolerances of users get higher.

Opt-saturated and Opt-unsaturated. We define two notions, *opt-saturated* and *opt-unsaturated*, which characterize the regimes under which *how much traffic is imposed on the network for the equilibrium price*. In general, as traffic demand gets higher compared to the 3G capacity, the network becomes *opt-saturated*, and vice versa. The main reason for introducing those two notions is because the analysis becomes different depending on the volume of network traffic and the market behaves differently, and thus, the way of increasing the revenue and the net-utility can be differently interpreted. For a formal definition, we first recall that \mathcal{P} is the set of all

feasible prices, defined by provider rationality and capacity constraint, or,

$$\mathcal{P} \triangleq \{p \mid R(p) > 0, Y(t; p) \leq C_{3g}, \forall t \in T\}. \quad (6)$$

Definition 4.2 (Opt-saturated and Opt-unsaturated): Let p^* be an *equilibrium price* that maximizes the revenue, i.e., $p^* \in \arg \max_{p \in \mathcal{P}} R(p)$. The network is said to be *saturated* at p , if $\max_{t \in T} Y(t; p) = C_{3g}$. For a *unique* equilibrium price p^* , the network is said to be *opt-saturated* if the network is saturated at p^* , and *opt-unsaturated* otherwise.

Let p_0 be the *threshold price* above which all the feasible prices lie, i.e., $p_0 = \inf_{p \in \mathcal{P}} p$. For a given price p , $R(p) > 0$ implies $\max_{t \in T} Y(t; p) > 0$, since no user subscription or no traffic results in zero income to the provider. Note that p^* is not necessarily equal to p_0 . Let $A(p) = \max_{t \in T} Y(t; p)$ be the total 3G traffic at *peak* time. Note that $A(p)$ is decreasing in p . Since $A(p)$ is decreasing in p , a feasible price in \mathcal{P} is greater than or equal to p_0 .

B. Flat pricing

This subsection considers the impact of offloading when flat pricing is used. In flat pricing, a user pays a flat fee p regardless of its 3G traffic usage if it subscribes to the 3G service. Since there is no incentive to discourage excessive network traffic, the traffic volume generated by a user equals to its traffic demand; $x_\Phi(t) = \phi(t)$ for a subscribing user with total traffic demand Φ , where $\phi(t)$ is the traffic demand at slot t split from Φ .

A user with traffic demand Φ maximizes its net-utility:

$$\sum_{t \in T} \gamma(t) x_\Phi(t)^\theta - p = \sum_{t \in T} w(t)^{1-\theta} \phi(t)^\theta - p = \Phi^\theta - p, \quad (7)$$

since $\gamma(t) = w(t)^{1-\theta}$ by **A3**, $x_\Phi(t) = \phi(t)$, for all t , and the temporal preference $w(t) = \frac{\phi(t)}{\Phi}$. From (3), the provider maximizes its revenue:

$$\begin{aligned} R(p) &= \hat{N} p \int_{\frac{1}{p}^\theta}^{\Phi_{\text{max}}} dF_\Phi - \hat{N} \eta \kappa_{\text{avg}} \int_{\frac{1}{p}^\theta}^{\Phi_{\text{max}}} \Phi dF_\Phi \\ &= \hat{N} \int_{\frac{1}{p}^\theta}^{\Phi_{\text{max}}} (p - \eta \kappa_{\text{avg}} \Phi) dF_\Phi, \end{aligned} \quad (8)$$

where $\frac{1}{p}^\theta$ is the lowest traffic demand of a subscriber (i.e., positive net-utility and thus $\Phi^\theta > p$). No users subscribe if the price is too high, i.e., if $p \geq p_{\text{max}}$ from (7), where $p_{\text{max}} = \Phi_{\text{max}}^\theta$. Then, we should have that $\mathcal{P} \subset [0, p_{\text{max}})$.

Our main results, Prop. 4.1 and Theorem 4.1, state how the economic values (e.g. price and revenue) change by offloading. Prop. 4.1 characterizes (i) $R(p)$ and the feasible price set, and (ii) the equilibrium prices in the opt-saturated case and (iii) the opt-unsaturated case. Theorem 4.1 states that offloading is economically beneficial for the users, the provider, and the regulator.

Proposition 4.1 (Equilibrium Price in Flat): If the cost coefficient $\eta < (\kappa_{\text{avg}} \Phi_{\text{max}}^{1-\theta})^{-1}$,

- (i) $R(p)$ is unimodal⁷ over $[0, p_{\text{max}})$, and the feasible price set \mathcal{P} is non-empty and connected.

⁶When we emphasize that $Y(t)$ (resp. $X(t)$) depends on a given price p , $Y(t; p)$ will be used instead of $Y(t)$ (resp. $X(t; p)$).

⁷A function $f(x)$ is called unimodal, if for some value v , it is monotonically increasing for $x \leq v$ and monotonically decreasing for $x \geq v$.

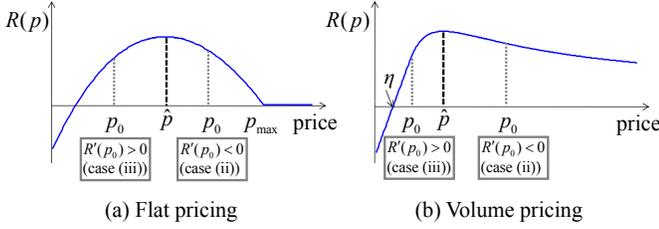


Fig. 2. Revenue function $R(p)$ in flat and volume pricing. The p_{\max} is the highest price above which no user subscribes in flat pricing, \hat{p} is the unique solution of $\frac{\partial R(p)}{\partial p} = 0$, and η is the network cost coefficient. The achievable revenue (at equilibrium) is not always at \hat{p} , since \hat{p} may not be in the feasible price set, which is determined by capacity constraint and provider rationality.

- (ii) The network is *opt-saturated*, if $R'(p_0) < 0$, where the unique equilibrium price $p^* = p_0$, where $p_0 = \Phi_{\max}^{\theta} \left(1 - \frac{C_{3g}}{\kappa_{\text{peak}} \hat{N} \mathbb{E}[\Phi]}\right)^{\frac{\theta}{2-\sigma}}$.
- (iii) The network is *opt-unsaturated*, if $R'(p_0) > 0$, where the unique equilibrium price $p^* = p^*(\kappa_{\text{avg}})$ is such that $\frac{\partial R(p)}{\partial p} \Big|_{p=p^*} = 0$, and $\frac{\partial p^*(\kappa_{\text{avg}})}{\partial \kappa_{\text{avg}}} > 0$.

Theorem 4.1 (Economic Gain from Offloading in Flat):

If $\eta < (\kappa_{\text{avg}} \Phi_{\max}^{1-\theta})^{-1}$, the net-utilities of all subscribers and the provider's revenue at equilibrium increases (thus the user surplus and the social-welfare increase), as (i) κ_{peak} decreases in the opt-saturated case, and (ii) as κ_{avg} decreases in the opt-unsaturated case.

The proof is presented in the Appendix. Here, we briefly interpret Prop. 4.1 and Theorem 4.1. First, clearly if the network cost is too high, the provider cannot achieve any positive revenue, where the condition of $\eta < (\kappa_{\text{avg}} \Phi_{\max}^{1-\theta})^{-1}$ guarantees the existence of prices under which the revenue is positive. This condition is relaxed as more offloading occurs (i.e., κ_{avg} decreases), resulting in less restricted business condition with positive revenue from the provider's perspective. Second, every feasible price is larger than or equal to the threshold price p_0 . Also, $R(p)$ is unimodal and \mathcal{P} is connected. Thus, at the threshold price, if $R'(p_0) < 0$, then $R(p_0) \geq R(p)$ for all $p \in \mathcal{P}$ (see Fig. 2(a)). Thus, the equilibrium price is unique, and $p^* = p_0$, where p_0 is characterized as in Prop. 4.1(ii). Also, the network is opt-saturated if $R'(p_0) < 0$, because the peak traffic volume $A(p_0) = C_{3g}$ (otherwise, there exists a smaller feasible price than p_0). Now, if $R'(p_0) > 0$, the equilibrium price p^* is such that $R'(p^*) = 0$, as in Prop. 4.1(iii). Again, this case makes the network opt-unsaturated because $A(p^*) < A(p_0)$ (due to decreasing property of $A(p)$ in p) and $A(p_0) \leq C_{3g}$.

We now explain the relationship between traffic demand and opt-saturatedness. The amount of total traffic demand of users affects the revenue change rate at the *traffic-maximizing* price, $R'(p_0)$, where 3G capacity and offloading indicators are fixed. If traffic demand is high enough, when the provider can reduce its flat fee (by offloading or network upgrade), revenue increases even with the reduced price, i.e., $R'(p_0) < 0$, since increase of subscribers exceeds price reduction. In other words, when $R'(p_0) < 0$, if the provider increases its flat price from p_0 , the provider revenue decreases, since the revenue reduction from the reduced number of subscribers is greater than the revenue increase from the increased price.

If traffic demand is not significantly high, subscription ratio does not increase drastically, so that revenue decreases, i.e., $R'(p_0) > 0$, and at the optimal price, the 3G capacity is not fully utilized by the users, i.e., if the provider increases its flat price from p_0 , revenue increase from the increased price is greater than revenue reduction from the reduced number of subscribers, and p_0 is not the price at the equilibrium.

Using the results of Prop. 4.1, Theorem 4.1 states that offloading is economically beneficial from the perspective of the users, the provider, and the regulator, where the mechanisms behind the increase in the revenue are different in the opt-saturated and opt-unsaturated cases. In the opt-saturated case, as more 3G traffic is offloaded through WiFi at *peak* time, i.e., κ_{peak} decreases, the provider turns out to have extra 3G capacity. Then, the provider attracts more subscribers by lowering its flat fee, in order to utilize the extra capacity. As the increase in the number of subscribers exceeds the reduced price, the revenue increases. Indeed, from Prop. 4.1(ii) the equilibrium price decreases as κ_{peak} decreases. The net-utility increases for all subscribers by price reduction since a subscribing user in flat pricing always generate all the traffic demand. In the opt-unsaturated case, the number of subscribers does not increase drastically even if the provider decreases its flat fee, so that the provider's income does not increase. However, the network cost decreases substantially as the 3G traffic decreases, i.e., κ_{avg} decreases, and the revenue increases. Since the equilibrium price still decreases, as κ_{avg} decreases from Prop. 4.1(iii), the net-utility increases for all subscribers by the same argument as in the opt-saturated case.

C. Volume pricing

In volume pricing, user payment is proportional to its 3G traffic volume. For a given unit price, a user chooses the amount of traffic that maximizes its net-utility. In this subsection, for tractability, we focus more on the average analysis by assuming that per-user and -time dependence of delay profile and WiFi connection probability are homogeneous, i.e., $\alpha_{\Phi}^d = \alpha^d$, $e_{\Phi}^d(t) = e^d$ for all t and all users. Then, by (5), for a user with traffic demand Φ ,

$$\sum_{t \in T} y_{\Phi}(t) = \sum_{t \in T} \left(x_{\Phi}(t) \sum_{d=0}^D \alpha^d (1 - e^d) \right) = \kappa_{\text{avg}} \sum_{t \in T} x_{\Phi}(t), \quad (9)$$

where note that $\kappa_{\text{avg}} = \sum_{d=0}^D \alpha^d (1 - e^d)$ by the definition in (4). A user with traffic demand Φ pays $p \sum_{t \in T} y_{\Phi}(t)$ and maximizes the following net-utility (for a given price p):

$$\begin{aligned} & \sum_{t \in T} \gamma(t) x_{\Phi}(t)^{\theta} - p \sum_{t \in T} y_{\Phi}(t) \\ &= \sum_{t \in T} w(t)^{1-\theta} x_{\Phi}(t)^{\theta} - p \kappa_{\text{avg}} \sum_{t \in T} x_{\Phi}(t) \end{aligned} \quad (10)$$

using $\gamma(t) = w(t)^{1-\theta}$ and (9). Since users pay in proportion to the volume of 3G traffic, a notion of *payment per unit (3G + WiFi) traffic* is useful, given by:

$$\frac{p \sum_{t \in T} y_{\Phi}(t)}{\sum_{t \in T} x_{\Phi}(t)} = \frac{p \kappa_{\text{avg}} \sum_{t \in T} x_{\Phi}(t)}{\sum_{t \in T} x_{\Phi}(t)} = p \kappa_{\text{avg}},$$

where without offloading, i.e., $\kappa_{\text{avg}} = 1$, payment per unit traffic is just p . From (3), the provider maximizes its revenue

$$R(p) = \hat{N}(p - \eta) \int_0^{\Phi_{\max}} \sum_{t \in T} y_{\Phi}(t) dF_{\Phi}. \quad (11)$$

Since $R(p) \leq 0$ for $p \leq \eta$, we should have $\mathcal{P} \subset (\eta, \infty)$. It is clear that as the payment per unit traffic $p\kappa_{\text{avg}}$ decreases, the traffic which can be delivered per dollar increases. We will show that the payment per unit traffic $p\kappa_{\text{avg}}$ decreases, as more offloading through WiFi occurs.

Similarly in flat pricing, we present our main results by Prop. 4.2 and Theorem 4.2. Prop. 4.2 characterizes the equilibrium prices in opt-saturated and opt-unsaturated cases. Theorem 4.2 states that offloading is economically beneficial for the users, the provider, and the regulator.

Proposition 4.2 (Equilibrium Price in Volume):

- (i) $R(p)$ is unimodal for $p \geq \eta$ and the feasible price set \mathcal{P} is non-empty and connected.
- (ii) The network is *opt-saturated*, if $R'(p_0) < 0$, where the unique equilibrium price is $p^* = p_0$ where $p_0 = p_0(\kappa_{\text{peak}})$ is the threshold price, and $\frac{\partial p_0(\kappa_{\text{peak}})}{\partial \kappa_{\text{peak}}} > 0$.
- (iii) The network is *opt-unsaturated*, if $R'(p_0) > 0$, where the unique equilibrium price $p^* = p^*(\kappa_{\text{avg}})$ is such that $\frac{\partial R(p)}{\partial p} \Big|_{p=p^*} = 0$, and $\frac{\partial (p^*(\kappa_{\text{avg}})\kappa_{\text{avg}})}{\partial \kappa_{\text{avg}}} > 0$.

Theorem 4.2 (Economic Gain from Offloading in Volume):

The net-utilities for all users and the provider's revenue increase (thus the user surplus and the social-welfare increase), (i) as κ_{peak} decreases, in the opt-saturated case, and (ii) as κ_{avg} decreases, in the opt-unsaturated case.

The proof is presented in the Appendix. Here, we briefly interpret Prop. 4.2 and Theorem 4.2. Note that different from in flat pricing, in volume pricing, $\mathcal{P} \neq \emptyset$ for *any* network cost coefficient η and all users subscribe to the service. The revenue function is unimodal (see Fig. 2(b)), so that our analysis becomes significantly convenient, and as in flat pricing, $R'(p_0)$, determines whether the threshold price p_0 is the price at equilibrium or not. The relationship between the traffic demand and opt-saturatedness is analogous to that in flat pricing, where basically a high traffic demand induces opt-saturatedness. We also see that as the offloaded traffic increases, the payment per unit traffic decreases in both opt-saturated and opt-unsaturated cases.

In the opt-saturated case, we experience the revenue increase similarly to flat pricing. In this case, offloading generates extra 3G capacity, thereby the provider attracts more traffic by reducing the unit price to get higher revenue. Note that in flat, higher revenue is due to more subscribing users by reducing the flat fee. Indeed, from Prop. 4.2(ii), the equilibrium price p^* decreases as κ_{peak} decreases. However, in the opt-unsaturated case, flat and volume pricing behave differently. Unlike the flat pricing, as 3G traffic is reduced by offloading, the provider's income decreases in volume pricing. Then, the provider increases the price to compensate for the revenue decrease, which, however, does not bring decrease in income for the following reasons: even though the price p is increased, 3G+WiFi traffic is not reduced as long as the payment per unit traffic $p\kappa_{\text{avg}}$ is not increased. Thus, the total income $p\kappa_{\text{avg}} \times \text{traffic}$ (3G+WiFi) remains the same if the $p\kappa_{\text{avg}}$ is the same. Since cost is proportional to 3G traffic, reduced 3G traffic leads to cost reduction which is the main factor to the revenue increase. The payment per unit traffic at equilibrium $p^*(\kappa_{\text{avg}})\kappa_{\text{avg}}$ decreases as κ_{avg} decreases from Prop. 4.2(iii).

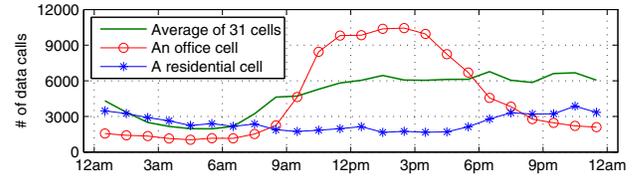


Fig. 3. The number of data calls on average and in office/residential cells.

V. TRACE-DRIVEN NUMERICAL ANALYSIS

A. Setup

In this subsection, we describe the setup for our trace-driven numerical analysis, such as the real traces and the parameter values. The duration of a time slot is set to be an hour, i.e., $T = 24$. The number of BS cells is 31 and the average number of users per cell is 1000,⁸ thus total 31000 users. The choice of 31 cells is due to a real trace which will be explained later. We test two cellular capacities, 8 Mbps for 3G and 32 Mbps for 4G, where the 4G capacity is projected to be about four times the 3G capacity [25].⁹ We set the price sensitivity $\theta = 0.5$ and the cost coefficient $\eta = 0.1$. We use two real traces to get the statistics of users' traffic and WiFi connection probability.

Trace 1 (3G traffic usage). The first trace is from a major cellular provider in Korea and includes the information on the number of high speed downlink/uplink packet access (HSDPA/HSUPA) calls, recorded every hour, in each of the 31 BSs in a day. Fig. 3 shows the average number of calls per hour over 31 BSs, and that in an office and a residential cell, where we regard a cell as an office cell if the call arrival at daytime (8:00 a.m. - 8:00 p.m.) exceeds that at night, and a residential cell otherwise. There exist 15 office and 16 residential cells. Assuming that the average data consumption per each call is similar over cells and time slots, we regard the number of data calls as the amount of traffic demand at each cell and slot.

Trace 2 (WiFi connection). The second trace is measured by 93 iPhone users from an iPhone user community in Korea, who volunteer and record their time-varying WiFi connectivity and locations, periodically scanned and recorded at every 3 minutes for two weeks [4]. Occupations of participants were diverse, e.g. students, daytime workers, and freelancers, as well as residential areas were, where half of participants lived in Seoul. We only recorded APs to which users can transmit data by sending a ping packet to our server. i.e., the trace only captures accessible WiFi APs that are open or users have authority.

We now present the main parameters based on the traces 1, 2 and the measurement results revealed in other research.

(a) Traffic demand (ϕ_i) and willingness to pay ($\gamma_i(t)$): Most measurements on mobile data [21], [22], [26], [27] showed that the user traffic volume follows an upper-truncated power-law distribution as used in the analysis of Section IV. Thus, we use an upper-truncated power-law distribution¹⁰ with exponent $\sigma = 0.57$ (which is observed in [22]), as the distribution of total daily traffic demand Φ_i by scaling the average, so that the per-month average ranges from 93 MB to 5.2 GB. Note that

⁸This is a typical number of users in a macro BS. For example, Sprint has 66,000 BSs and 55 million subscribers at the end of 2011 [23], [24].

⁹Yet, we still use the notation C_{3g} for notational simplicity.

¹⁰ $f_{\Phi}(x) = x^{-\sigma}/Z$, for $0 \leq x \leq \Phi_{\text{max}}$, where Φ_{max} is the maximum value of Φ and $Z = \frac{\Phi_{\text{max}}^{1-\sigma}}{1-\sigma}$.

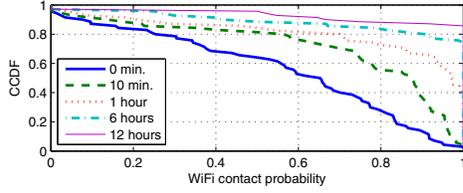


Fig. 4. The CCDF of WiFi contact probability of user i at slot t for various deadlines d , $e_{i,d}(t)$. The mean for each distribution is 0.56, 0.71, 0.80, 0.88, and 0.92, and the median for each distribution is 0.62, 0.87, 0.97, 1, and 1.

in [1], 1.3 GB/month is projected in year 2015. The temporal preference ($w_i(t) = \phi_i(t)/\Phi_i$) of users follows the average temporal usage pattern in trace 1. Users' willingness to pay is set to include some randomness across users, and its time-dependence is set to be proportional to temporal preference, i.e., $\gamma_i(t) = \nu_i w(t)^{1-\theta}$, where ν_i is uniformly distributed over $(0, 1)$.

(b) **WiFi connection probability** ($e_i^d(t)$): We use the trace 2 to obtain the values of ($e_i^d(t) : i \in N, t \in T$). Since trace 2 includes only 93 users, we repeatedly use their individual traces to generate N users' data, i.e., about $N/93$ users have the same $e_i^d(t)$. We refer the readers to [4] to know how often users meet WiFi in the experiment. To show the average pattern of $e_i^d(t)$, for each deadline d , we draw the CCDF of WiFi contact probability in Fig. 4. For 10 mins and 6 hours deadline, the average WiFi contact probabilities are 0.7 and 0.88, and the medians are 0.87 and 0.97, respectively.

(c) **BS association** ($s_i(t)$): The information on cell-level mobility is important in our model due to the (i) cell-level capacity constraint C_{3g} (which requires to track the number of users in a cell) and (ii) congestion pricing (which applies difference prices depending on spatio-temporal information). Unfortunately, trace 1 does not include users' cell-level mobility mainly because of privacy, thus we combine trace 1 with the statistics from [21] that has the distribution on the number of distinct BSs visited by a user per day. At the first time slot, we assign user associations so that the number of users in each cell at the first time slot is proportional to the traffic volume of the cell at that slot (e.g. 8 a.m.) in trace 1. We assign handover probabilities (from the associated cell to other cells) to users so that (i) the expected number of users in each cell at the next time slot is proportional to the traffic volume in trace 1 and (ii) the number of visited BSs follows the statistics in [21], assuming that handovers are uniformly distributed among time slots.

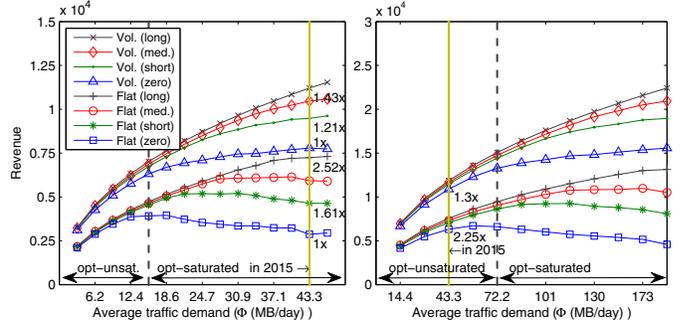
(d) **Delay profile** (α_i^d): To model the delay profile of users, we use various scenarios, such as *no-deadline*, *short*, *medium*, and *long*, where each scenario consists of four different classes (Video, Data, P2P, and Audio), as classified by Cisco [1]. The details are described in Table II. We consider the economic impact of WiFi offloading for two cases in our numerical results: (i) all users are uniformly given a scenario, e.g., *medium*, and (ii) there is a fixed portion of users for each scenario.

B. Results

Our numerical results quantify the benefits of delayed WiFi offloading in various aspects. We present our results by summarizing the key observations.

TABLE II
TRAFFIC CLASSIFICATION PROJECTED IN YEAR 2015 FROM CISCO [1]
AND ASSIGNED DEADLINES FOR EACH TRAFFIC CLASS. SC: SCENARIO

	Video	Data	P2P	Audio (VoIP)	Total
Ratio	66.4 %	20.9 %	6.1 %	6.6 %	100 %
SC:zero	0 sec.	0 sec.	0 sec.	0 sec.	-
SC:short	10 min.	30 min.	10 min.	0 sec.	-
SC:medium	30 min.	1 hour	30 min.	0 sec.	-
SC:long	2 hours	6 hours	2 hours	0 sec.	-



(a) $C_{3g} = 3.6$ GB/hour (8 Mbps) (b) $C_{3g} = 14.4$ GB/hour (32 Mbps)

Fig. 5. Flat and volume pricing: revenue for various delay profiles in Table II and traffic demand, with different cellular capacities, where users experience a single scenario in Table II. Delay profiles are set to be the same across all users. Offloading indicators are decreasing as delay tolerance gets higher (from short to long), where $\kappa_{avg} = .44, .28, .23, .15$ and $\kappa_{peak} = .0044, .0026, .0020, .0013$ for zero, short, medium, and long scenarios. The numbers (-x) represent the increase of revenue by (a) delayed offloading or (b) network upgrade (from 3G to 4G). Opt-saturatedness is determined by the traffic demand and cellular capacity, where the dotted line shows the threshold in the on-the-spot offloading over flat pricing.

1) **Revenue in volume pricing exceeds that in flat pricing by applying delayed WiFi offloading, but the revenue increase is higher in flat pricing than volume pricing:** Fig. 5(a) depicts the revenue of flat and volume for various traffic demand and delay profiles, where users experience a single scenario. Revenue in volume exceeds that in flat in all cases, because in flat, a subscriber with high traffic demand generates heavy traffic and dominates the network resources without paying more fees to the provider, whereas in volume, user payment is proportional to traffic volume, so that if a subscriber generates heavy traffic, the payment is high. This imposes *negative externality* (i.e., congestion) to the provider and reduces provider revenue. However, the revenue *increase* of delayed offloading, which is the amount of increased revenue over revenue in the on-the-spot offloading, is higher in flat. The revenue increase in flat pricing is about 61-152%, whereas the revenue increase in volume pricing is about 21-43%, when the average traffic demand is 43.3 MB/day (1.5 GB/month). This is because in flat pricing, 3G traffic reduction does not affect the provider's income, whereas, in volume pricing, 3G traffic reduction decreases the income. We also depict the revenue of flat and volume pricing when users have a mixture of four scenarios of delay deadline in Fig. 6. We find that as user portion with high delay tolerance increases, revenue increases in both flat and volume pricing. From this result, we find that even when some portion of users are delay-tolerant, the single provider can increase its revenue and all subscribers, including non-delay-tolerant users, benefit from the reduced price.

2) **The revenue gain from on-the-spot to delayed offloading is similar to that generated from upgrading the network capacity by a factor of 4:** Fig. 5 depicts revenue of flat

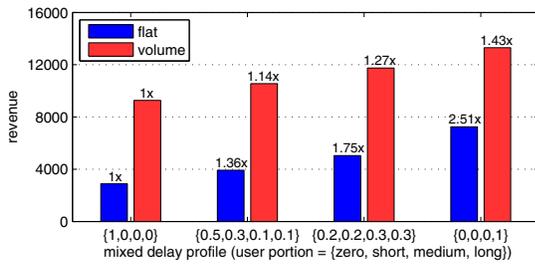
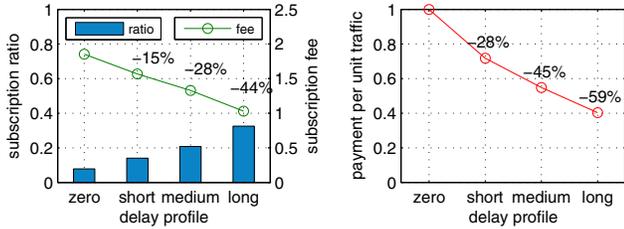


Fig. 6. Revenue in flat and volume pricing with various mixed delay profiles, where user portions of scenarios (zero, short, medium, long) are different. The average traffic demand is 43.3 MB/day (1.5 GB/month) and 3G capacity is 3.6 GB/hour. The numbers (-x) represent the increase of revenue compared to the revenue in on-the-spot offloading.



(a) Flat: fee and subscription ratio (b) Volume: payment per unit traffic

Fig. 7. Change of flat price and subscription ratio in flat pricing, and payment per unit traffic in volume pricing. The average traffic demand is 43.3 MB/day (1.5GB/month) and 3G capacity is 3.6 GB/hour (opt-saturated).

and volume pricing for various traffic demand, with different cellular capacities. As the traffic demand increases, the network gets congested and eventually becomes opt-saturated. If a provider upgrades the cellular network capacity by a factor of 4, the revenue increases by 115% in flat and 30% in volume, respectively, when the traffic demand is 43.3 MB/day. We recall that the revenue gain of offloading in flat and volume pricing is 61-152% and 21-43%, which is as significant as the revenue gain from upgrading network capacity by a factor of 4. Thus, if traffic demand is high compared to capacity, adopting delayed offloading can be a good solution to increase revenue, where the network upgrade induces huge installation costs. Note that when traffic demand is not high (i.e., opt-unsaturated), the revenue increase is small both in network upgrade and delayed offloading.

3) As more traffic is offloaded, the flat price decreases and subscription ratio increases simultaneously in flat pricing, and payment per unit traffic decreases in volume pricing: As shown in Fig. 7, the flat fee decreases by 15-44% and subscription ratio increases accordingly in flat pricing, and payment per unit traffic decreases by 28-59% in volume pricing, when the average traffic demand is 1.5 GB/month (opt-saturated). In the opt-unsaturated case, price reduction is not drastic both in flat and volume pricing, since the *income* does not increase by price reduction due to low traffic demand. The reduction in flat price and payment per unit traffic induces increase in user surplus, as shown in Fig. 8.

4) Two-tier and congestion pricing increase the revenue, compared to flat and volume pricing, but such gains become smaller, as more traffic is offloaded: Fig. 8 shows the change of revenue, surplus, and welfare in four pricing schemes. It is intuitive that as pricing granularity increases in terms of price (from flat to tiered) or space/time (from volume to congestion), revenue increases, because the provider has more degree of

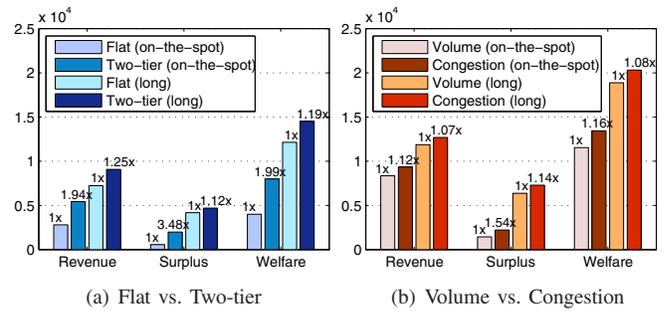


Fig. 8. The revenue, surplus, and welfare in flat, tiered, volume and congestion pricing. The number (-x) above each bar represents the increase compared to the revenue in (a) flat or (b) volume pricing. The average traffic demand is set to be 43.3MB/day (1.5GB/month) which is projected in year 2015 by Cisco and the 3G capacity is 3.6GB/hour.

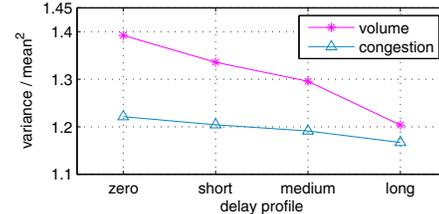
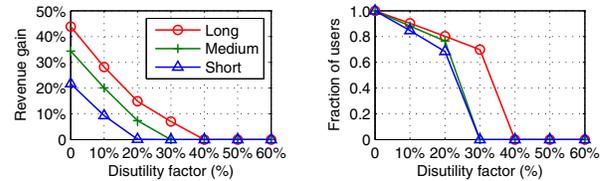


Fig. 9. Variance of normalized cell load at each time slot.



(a) Decrease in the revenue gain. (b) Decrease in the fraction of delayed offloading users.

Fig. 10. Effect of delay disutility on (a) the revenue gain and (b) the fraction of delayed offloading users.

freedom to control the market. However, the rate of increase diminishes as more traffic is offloaded through WiFi. Using the traffic demand in 2015, the revenue in two-tier pricing is greater than that in flat pricing by 94% and 25% in on-the-spot and delayed offloading, resp., where the revenue in congestion pricing is greater than that in volume pricing by 12% and 7% in on-the-spot and delayed offloading, resp. We also find that delayed offloading reduces spatiotemporal imbalance by dispersing traffic to other time and locations, so that the effect of space/time-varying price is reduced. To see this, we depict the variance of normalized cell load at each time in Fig. 9, where the variance decreases as more traffic is offloaded. As a result, the time-flattening effect and revenue increase of congestion pricing decrease, since congestion pricing performs better when temporal imbalance in traffic demand is severe.

5) As users' utilities are decreased by the delay disutility, the revenue gain from delayed offloading decreases, but the decrease in revenue gain is less severe when users have higher delay tolerance: Here, we try to understand the effect of delay disutility on revenue gain by applying the *disutility factor* in user utility. We consider the volume pricing and assume that utilities of users who perform delayed offloading are decreased by the *disutility factor* (%) from the original utility without delayed offloading. A user can decide whether it adopts delayed offloading or not, based on the net-utility, i.e., a user adopts delayed offloading only if the price discount

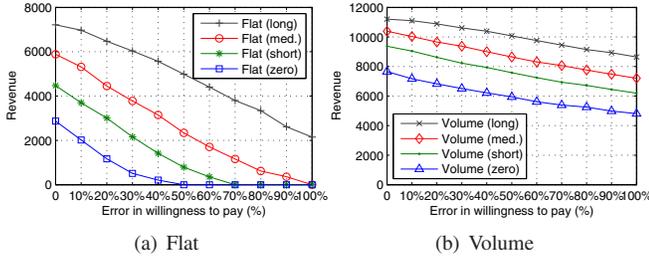


Fig. 11. Change of revenue in flat and volume pricing when the provider overestimates willingness to pay of users. The average traffic demand is 43.3 MB/day (1.5GB/month) and 3G capacity is 8Mbps (3.6 GB/hour) (opt-saturated).

is higher than the amount of disutility, where the price discount is only given to users who adopt delayed offloading. We depict the revenue gain and the fraction of users who adopt delayed offloading, in Fig. 10. Both the revenue gain and the delayed offloading ratio decrease as the *disutility factor* increases. We still obtain more than 50% of the revenue gain when users have less than 15% and 10% of disutility factor, for the *long* and *short* delay profiles, respectively. Note that users will experience less disutility for shorter delay. When the disutility factor is higher than 40%, no user decides to use delayed offloading, so that the revenue gain is zero.

6) If the provider overestimates willingness to pay of users, the provider revenue decreases, but the decreasing rate becomes smaller with delayed offloading: In all the above simulation results, we assume that the provider has complete information of user profiles. But there can be misinformation of user profiles in practical settings. In this section, we see the effect of misinformation in willingness to pay (i.e., user utility) on the provider revenue. We depict the provider revenue in flat and volume pricing in Fig. 11 when the provider overestimates willingness to pay of users. We find that as the error in willingness to pay increases, the provider revenue decreases in both flat and volume pricing as the provider chooses a price that is higher than the price at the equilibrium point with complete information, but the decreasing rate is higher in flat than volume pricing. In other words, volume pricing is less sensitive to misinformation in willingness to pay than flat pricing. Also, we find that as the delay deadline gets larger, the negative effect of misinformation in willingness to pay on the provider revenue becomes less severe (especially in flat pricing).

VI. CONCLUDING REMARK AND FUTURE WORK

In this paper, we model a game-theoretic framework to study the economic aspects of WiFi offloading, where we drew the following messages from the analytical and numerical studies: (a) WiFi offloading is economically beneficial for both the provider and users, where the increase ranges from 21% to 152% in the provider revenue and from 73% to 319% in the users' surplus. (b) The revenue gain from on-the-spot to delayed offloading is similar to that generated by the network upgrade from 3G to 4G. (c) The revenue increase of complex pricing schemes (such as two-tier from flat, and congestion from volume), becomes smaller for higher offloading chances, which is true as of now and in the future, when more WiFi APs are expected to be deployed.

Another well-known benefit from WiFi offloading is transmission energy saving, which is shown in [4], [28]. It is shown in [4] that 50-60% of transmission energy can be reduced for 1-hour delay, which in turn increases users' battery lifetime. Even if we do not consider this benefit in this paper, it is obvious that a user benefits from the increased battery lifetime.

There are a few limitations in our work. Our results rely on the assumption that network traffic has a degree of delay tolerance and users can tolerate some amount of delay, where delay depends on the class of traffic (even if we provide the numerical results of a mixture of users with different delay scenarios, including ones requiring no delay deadline). Also, some economic parameter values (e.g., willingness to pay and price sensitivity) are arbitrarily chosen from (i) the lack of appropriate measurement data (e.g., cellular providers do not make public the payment of individual users mainly from the privacy of users) and (ii) the difficulty in quantification of parameters (especially for economic parameters). Thus, our results can sometimes be regarded as an upper-bound on the economic benefits of WiFi offloading. A simple way of reflecting user dissatisfaction from delay would be to design a net-utility function which jointly captures the happiness by data transmission and the disutility by delay such as [8], [9], which we leave as a future work. We assume perfect information of user profiles (e.g., willingness to pay, WiFi connection probability), but there can be misinformation of user profiles (as in our simulation result 6) in Section V-B with misinformation in willingness to pay). Thus, we regard a Bayesian game model in which information of other players is incomplete, as a future work. Another future work is to consider multiple providers, where they have different plans to overcome the mobile data explosion (e.g. delayed offloading, network upgrade, or complex pricing).

APPENDIX

A. Proof of Proposition 4.1

Step 1: Unimodality of $R(p)$. In flat pricing, the total 3G traffic volume of a 3G-subscribing user is equal to its total traffic demand, i.e., $\sum_{t \in T} x_{\Phi}(t) = \sum_{t \in T} \phi(t) = \Phi$, and the user enters the market only when $\Phi > p^{\frac{1}{\theta}}$, from (7). Based on it, we first express $\sum_{x \in T} X(t)$ and $A(p)$ using the parameters of the traffic demand distribution. We first have:

$$\sum_{t \in T} X(t) = \hat{N} \int_{p^{\frac{1}{\theta}}}^{\Phi_{\max}} \Phi f_{\Phi}(\Phi) d\Phi = \hat{N} \frac{\Phi_{\max}^{2-\sigma} - p^{\frac{2-\sigma}{\theta}}}{Z(2-\sigma)},$$

where $f_{\Phi}(\Phi) = \frac{\Phi^{-\sigma}}{Z}$ by **A2** and recall that $Z = \frac{\Phi_{\max}^{1-\sigma}}{1-\sigma}$. Then, by (4),

$$A(p) = \kappa_{\text{peak}} \sum_{t \in T} X(t) = \kappa_{\text{peak}} \hat{N} \frac{\Phi_{\max}^{2-\sigma} - p^{\frac{2-\sigma}{\theta}}}{Z(2-\sigma)}. \quad (12)$$

From (8), the revenue $R(p)$ is expressed as:

$$R(p) = \hat{N} p \left(1 - \frac{p^{\frac{1-\sigma}{\theta}}}{Z(1-\sigma)} \right) - \frac{\eta \kappa_{\text{avg}} \hat{N} \left(\Phi_{\max}^{2-\sigma} - p^{\frac{2-\sigma}{\theta}} \right)}{Z(2-\sigma)}.$$

Then, the first derivative of $R(p)$ is

$$\frac{\partial R(p)}{\partial p} = \hat{N} \left(1 - \frac{(1 + \frac{1-\sigma}{\theta}) p^{\frac{1-\sigma}{\theta}}}{Z(1-\sigma)} + \frac{\eta \kappa_{\text{avg}} p^{\frac{2-\sigma}{\theta} - 1}}{Z\theta} \right). \quad (13)$$

We can easily check that $R'(0) > 0$ and $R'(p_{\max}) < 0$ under the condition that $\eta < (\kappa_{\text{avg}} \Phi_{\max}^{1-\theta})^{-1}$ and from the intermediate value theorem, there exists a price $\hat{p} \in (0, p_{\max})$ such that $R'(\hat{p}) = 0$. Now, we show that $R(p)$ is unimodal, thereby \hat{p} is unique. The second derivative of $R(p)$ is

$$\frac{\partial^2 R(p)}{\partial p^2} = \hat{N} p^{\frac{1-\sigma-\theta}{\theta}} \frac{\eta \kappa_{\text{avg}} p^{\frac{1-\theta}{\theta}} (2-\theta-\sigma) - (1+\theta-\sigma)}{Z\theta^2}. \quad (14)$$

We have $\partial^2 R(p)/\partial p^2 < 0$ (concave) over $[0, \bar{p}]$, and $\partial^2 R(p)/\partial p^2 > 0$ (convex) over (\bar{p}, p_{\max}) , where $\bar{p} = \left(\frac{1+\theta-\sigma}{\eta \kappa_{\text{avg}} (2-\theta-\sigma)}\right)^{\frac{\theta}{1-\theta}}$, such that $\partial^2 R(p)/\partial p^2 = 0$. Since $R'(p_{\max}) < 0$ and $R'(p)$ is increasing over (\bar{p}, p_{\max}) from the convexity, $R'(p) < 0$ over (\bar{p}, p_{\max}) , and $R'(\bar{p}) < 0$. Thus, $\hat{p} \notin [\bar{p}, p_{\max})$. Since $R'(0) > 0$, $R'(\bar{p}) < 0$, and $R'(p)$ is decreasing over $[0, \bar{p})$ from the concavity, the solution of $R'(\hat{p}) = 0$, \hat{p} is unique and $\hat{p} < \bar{p}$. Also, $R(p)$ is unimodal over $[0, p_{\max})$ since $R'(p)$ has only one sign change.

Step 2: Characterization of \mathcal{P} . By definition of the set of feasible prices with provider rationality and capacity constraint, $\mathcal{P} = \mathcal{E} \cap \mathcal{F}$ where $\mathcal{E} = \{p \mid A(p) \leq C_{3g}\}$ and $\mathcal{F} = \{p \mid R(p) > 0\}$. From (12), $A(p)$ is decreasing in p . Thus, there exists some p_{\min} , such that $A(p) \leq C_{3g} \Leftrightarrow p \geq p_{\min}$. Therefore, $\mathcal{E} = \{p \mid p \geq p_{\min}\}$ which is a connected set. The p_{\min} is characterized as:

$$p_{\min} = \begin{cases} 0 & \text{if } A(0) < C_{3g} \\ \left(\Phi_{\max}^{2-\sigma} - \frac{C_{3g}Z(2-\sigma)}{N\kappa_{\text{peak}}}\right)^{\frac{\theta}{2-\sigma}} & \text{if } A(0) \geq C_{3g} \end{cases}$$

Note that $p_{\min} < \Phi_{\max}^{\theta}$ since $0 < \sigma < 1$. Regarding \mathcal{F} , we first recall that $p < p_{\max} = \Phi_{\max}^{\theta}$ since $R(p) = 0$ for $p \geq \Phi_{\max}^{\theta}$ (i.e., there exists no subscriber). Since $R(p)$ is unimodal over $[0, p_{\max})$, $\mathcal{F} = \{p \mid R(p) > 0\}$ is connected. There exists a unique $p_z < \hat{p}$ such that $R(p_z) = 0$, since $R(0) \leq 0$, $R(\hat{p}) > 0$ and $R(p)$ is strictly increasing ($R'(p) > 0$) in $0 \leq p \leq \hat{p}$. Hence $\mathcal{F} = (p_z, p_{\max})$ for $p_z < p_{\max}$ such that $R(p_z) = 0$. Since both \mathcal{E} and \mathcal{F} are connected, $\mathcal{P} = \mathcal{E} \cap \mathcal{F}$ is connected. Note that $p_0 = \inf\{p \mid R(p) > 0, A(p) \leq C_{3g}\} = \max\{p_{\min}, p_z\}$. If $R(p_0) > 0$, $p_0 \in \mathcal{F}$ and $\mathcal{P} = [p_0, p_{\max})$. If $R(p_0) = 0$, then, $p_0 \notin \mathcal{F}$. Thus, $p_0 = p_z$ and $\mathcal{P} = (p_0, p_{\max})$. From Steps 1 and 2, the result (i) holds.

Step 3: Proof of (ii). If $R'(p_0) < 0$, then $\hat{p} < p_0$, which means \hat{p} is not in \mathcal{P} , i.e., \hat{p} cannot be the equilibrium price. Since $R(p_{\max}) = 0$ and $R'(p) < 0$ for $p_0 \leq p \leq p_{\max}$ from unimodality of $R(p)$ we have $R(p_0) > 0$; $\mathcal{P} = [p_0, p_{\max})$. Therefore $p_0 = p_{\min}$ such that $A(p_{\min}) = C_{3g}$ and

$$\begin{aligned} p_0 &= \left(\Phi_{\max}^{2-\sigma} - \frac{C_{3g}Z(2-\sigma)}{\kappa_{\text{peak}}\hat{N}}\right)^{\frac{\theta}{2-\sigma}} \\ &= \Phi_{\max}^{\theta} \left(1 - \frac{C_{3g}}{\kappa_{\text{peak}}\hat{N}\mathbb{E}[\Phi]}\right)^{\frac{\theta}{2-\sigma}}, \end{aligned}$$

where $\mathbb{E}[\Phi] = \frac{1-\sigma}{2-\sigma}\Phi_{\max}$. Since $R(p)$ is decreasing over \mathcal{P} , $R(p)$ is maximum at p_0 , that is, p_0 is the unique equilibrium price. Since $A(p_0) = C_{3g}$, the network is *opt-saturated*.

Step 4: Proof of (iii). If $R'(p_0) > 0$, then $\hat{p} > p_0$ since $R(p)$ is unimodal. From (12), $A(p)$ is a decreasing function of p . Hence $A(\hat{p}) < A(p_0) \leq C_{3g}$; the network is *opt-unsaturated*.

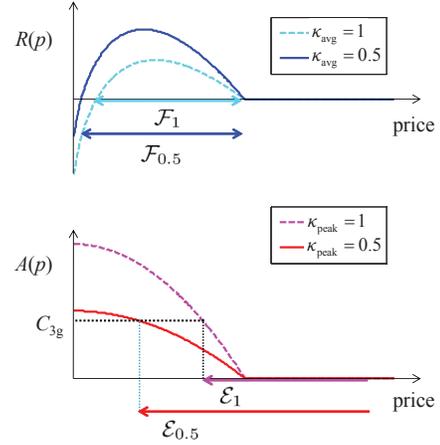


Fig. 12. Change of feasible price set, $\mathcal{P} = \mathcal{E} \cap \mathcal{F}$ for $\kappa_{\text{avg}} = 1$, $\kappa_{\text{peak}} = 1$ and $\kappa_{\text{avg}} = 0.5$, $\kappa_{\text{peak}} = 0.5$ in flat pricing.

We will show that the derivative $\frac{\partial \hat{p}}{\partial \kappa_{\text{avg}}}$ is positive. From (13) and taking a derivative of κ_{avg} w.r.t. p ,

$$\kappa_{\text{avg}} = \frac{1+\theta-\sigma}{1-\sigma} \hat{p}^{\frac{1-\sigma}{\theta}} - Z\theta, \quad \frac{\partial \kappa_{\text{avg}}}{\partial \hat{p}} = \frac{\hat{p}^{-\frac{2+\sigma}{\theta}}}{\eta(1-\sigma)} g(\hat{p}^{\frac{1-\sigma}{\theta}}),$$

where $g(z) = (2-\theta-\sigma)\Phi_{\max}^{1-\sigma} - \frac{(1-\theta)(1+\theta-\sigma)}{\theta}z$. To show $\frac{\partial \hat{p}}{\partial \kappa_{\text{avg}}} > 0$, it suffices to show $\frac{\partial \kappa_{\text{avg}}}{\partial \hat{p}} > 0$, for which we show $g(\hat{p}^{\frac{1-\sigma}{\theta}}) > 0$. From (13), we have

$$\begin{aligned} \hat{p}^{\frac{1-\sigma}{\theta}} &= \frac{\theta \Phi_{\max}^{1-\sigma}}{(1+\theta-\sigma) - \eta \kappa_{\text{avg}} (1-\sigma) \hat{p}^{\frac{1-\theta}{\theta}}} \\ &< \frac{\theta \Phi_{\max}^{1-\sigma}}{(1+\theta-\sigma) \left(1 - \frac{1-\sigma}{2-\theta-\sigma}\right)} \\ &= \frac{\theta(2-\theta-\sigma)}{(1-\theta)(1+\theta-\sigma)} \Phi_{\max}^{1-\sigma}, \end{aligned}$$

since $\hat{p} < \bar{p}$, where $\bar{p} = \left(\frac{1+\theta-\sigma}{\eta \kappa_{\text{avg}} (2-\theta-\sigma)}\right)^{\frac{\theta}{1-\theta}}$ such that $\partial^2 R(p)/\partial p^2 = 0$ from (14). Let $\rho = \frac{\theta(2-\theta-\sigma)}{(1-\theta)(1+\theta-\sigma)} \Phi_{\max}^{1-\sigma}$. Since $g(z)$ is decreasing as z is increasing and $g(\rho) = 0$, $g(\hat{p}^{\frac{1-\sigma}{\theta}}) > g(\rho) = 0$ since $\theta \in (0, 1)$ and $\sigma \in (0, 1)$. Thus, $\frac{\partial \kappa_{\text{avg}}}{\partial \hat{p}} > 0$ and $\frac{\partial \hat{p}}{\partial \kappa_{\text{avg}}}$ is also positive. ■

B. Proof of Theorem 4.1

(i) Opt-saturated. Recall that net-utility of a subscriber with Φ is $\Phi^{\theta} - p$, where $\Phi = \sum_{t \in T} \phi(t)$. Hence, the net-utility of a subscriber increases as p^* decreases from Proposition 4.1(i).

To study the impact of κ_{peak} , we regard κ_{peak} as a variable, not a constant. To show that $R(p^*)$ increases as κ_{peak} decreases, we will show that $\frac{\partial R(p^*)}{\partial \kappa_{\text{peak}}} < 0$. The first derivative of $R(p^*)$ with respect to κ_{peak} is,

$$\frac{\partial R(p^*)}{\partial \kappa_{\text{peak}}} = \frac{\partial R(p^*)}{\partial p^*} \frac{\partial p^*}{\partial \kappa_{\text{peak}}}.$$

From Proposition 4.1(ii), p^* is an increasing function in κ_{peak} . Therefore, it suffices to show that $\frac{\partial R(p^*)}{\partial p^*} < 0$, which is proved in the proof of Proposition 4.1(ii).

(ii) Opt-unsaturated. Using a similar argument in the proof of Theorem 4.1(i), the net-utility of a user and user surplus increase as κ_{avg} decreases, since the flat fee decreases as κ_{avg} decreases from Proposition 4.1(iii). In terms of the provider's revenue, we use the notations $R(p, \kappa_{\text{avg}})$ and $\mathcal{P}_{\kappa_{\text{avg}}}$ to explicitly

express the dependence of $R(p)$ and \mathcal{P} on κ_{avg} , because our interest lies in examining how $R(p)$ and \mathcal{P} change with varying κ_{avg} . First, $R(p, \kappa_{\text{avg}})$ increases as κ_{avg} decreases for $p \in [0, p_{\text{max}}]$, since differentiating by κ_{avg} yields:

$$\frac{\partial R(p, \kappa_{\text{avg}})}{\partial \kappa_{\text{avg}}} = -\frac{\eta \hat{N} \left(\Phi_{\text{max}}^{2-\sigma} - p^{\frac{2-\sigma}{\theta}} \right)}{Z(2-\sigma)} < 0. \quad (15)$$

Second, we will show that the set $\mathcal{P}_{\kappa_{\text{avg}}}$ gets “enlarged” as κ_{avg} decreases, for which it suffices to show that revenue increases. $\mathcal{P}_{\kappa_{\text{avg}}} = \mathcal{E} \cap \mathcal{F}_{\kappa_{\text{avg}}}$, where $\mathcal{E} = \{p \mid p \geq p_{\text{min}}\}$ and $\mathcal{F}_{\kappa_{\text{avg}}} = \{p \mid R(p, \kappa_{\text{avg}}) > 0\}$. Note that \mathcal{E} does not depend on κ_{avg} , but on κ_{peak} . Since $R(p, \kappa_{\text{avg}})$ is decreasing in κ_{avg} , $\mathcal{F}_{\kappa_{\text{avg}}}$ is enlarged as κ_{avg} decreases. Therefore, $\mathcal{P}_{\kappa_{\text{avg}}}$ is enlarged (or remains the same) and $\max_{p \in \mathcal{P}_{\kappa_{\text{avg}}}} R(p, \kappa_{\text{avg}})$ increases as κ_{avg} decreases. We illustrate this in Fig. 12. ■

C. Proof of Proposition 4.2

Step 1: Unimodality of $R(p)$. From (10),

$$U(x_{\Phi}) = \sum_{t \in T} (w(t)^{1-\theta} x_{\Phi}(t)^{\theta} - p \kappa_{\text{avg}} x_{\Phi}(t)). \quad (16)$$

Let $v(x_{\Phi}(t)) = w(t)^{1-\theta} x_{\Phi}(t)^{\theta} - p \kappa_{\text{avg}} x_{\Phi}(t)$. The net-utility $U(x_{\Phi})$ is maximized when $v(x_{\Phi}(t))$ is maximized for each t . At given t ,

$$\frac{\partial v(x_{\Phi}(t))}{\partial x_{\Phi}(t)} = \theta w(t)^{1-\theta} x_{\Phi}(t)^{\theta-1} - p \kappa_{\text{avg}},$$

$$\frac{\partial^2 v(x_{\Phi}(t))}{\partial x_{\Phi}(t)^2} = -\theta(1-\theta)w(t)^{1-\theta}x_{\Phi}(t)^{\theta-2}.$$

Since $\theta \in (0, 1)$, $\frac{\partial^2 v(x_{\Phi}(t))}{\partial x_{\Phi}(t)^2} < 0$. Therefore, $v(x(t))$ is concave in $x(t)$. Thus, at each time t , $v(x_{\Phi}(t))$ takes a unique maximum at

$$\begin{aligned} x_{\Phi}^*(t) &= \min \left\{ \phi(t), w(t) \left(\frac{\theta}{p \kappa_{\text{avg}}} \right)^{\frac{1}{1-\theta}} \right\} \\ &= w(t) \min \left\{ \Phi, \left(\frac{\theta}{p \kappa_{\text{avg}}} \right)^{\frac{1}{1-\theta}} \right\}. \end{aligned}$$

The second equality holds since $\phi(t) = w(t)\Phi$ and $\Phi = \sum_{t \in T} \phi(t)$. Moreover, it can be easily shown that $v(x_{\Phi}^*(t)) > 0$ for all t . This implies that a user with positive Φ subscribes the service and $x_{\Phi}^*(t) \neq 0$. Therefore,

$$\sum_{t \in T} x_{\Phi}^*(t) = \begin{cases} \Phi & \text{if } \Phi < \left(\frac{\theta}{p \kappa_{\text{avg}}} \right)^{\frac{1}{1-\theta}} \\ \Psi(p) & \text{if } \Phi > \left(\frac{\theta}{p \kappa_{\text{avg}}} \right)^{\frac{1}{1-\theta}} \end{cases}$$

where $\Psi(p) = \left(\frac{\theta}{p \kappa_{\text{avg}}} \right)^{\frac{1}{1-\theta}}$. Then, total user traffic over a day, $\sum_{t \in T} X(t)$ is as follows:

$$\begin{aligned} \sum_{t \in T} X(t) &= \hat{N} \int_0^{\Phi_{\text{max}}} \sum_{t \in T} x_{\Phi}^*(t) f_{\Phi}(\Phi) d\Phi \\ &= \hat{N} \left(\int_0^{\Psi(p)} \Phi f_{\Phi}(\Phi) d\Phi + \int_{\Psi(p)}^{\Phi_{\text{max}}} \Psi(p) f_{\Phi}(\Phi) d\Phi \right) \\ &= \begin{cases} \hat{N} \Psi(p) \left(1 - \frac{\Psi(p)^{1-\sigma}}{(2-\sigma)\Phi_{\text{max}}^{1-\sigma}} \right) & \text{if } \Psi(p) \leq \Phi_{\text{max}}. \\ \hat{N} \mathbb{E}[\Phi] & \text{if } \Psi(p) > \Phi_{\text{max}}. \end{cases} \end{aligned}$$

We denote

$$\begin{aligned} B(p) &= \sum_{t \in T} Y(t; p) = \kappa_{\text{avg}} \sum_{t \in T} X(t; p) \\ A(p) &= \max_{t \in T} Y(t; p) = \kappa_{\text{peak}} \sum_{t \in T} X(t; p). \end{aligned} \quad (17)$$

By (11), the revenue of the provider is $R(p) = (p - \eta)B(p)$.

We now show that $R(p)$ is unimodal over \mathcal{P} . Note that

$$\Psi(p) > \Phi_{\text{max}} \Leftrightarrow p < \theta(\kappa_{\text{avg}} \Phi_{\text{max}}^{1-\theta})^{-1}.$$

If $p < \theta(\kappa_{\text{avg}} \Phi_{\text{max}}^{1-\theta})^{-1}$, then $B(p)$ is a positive constant, $B(p) = \kappa_{\text{avg}} \hat{N} \mathbb{E}[\Phi]$, for all $p \in \mathcal{P}$ and $\frac{\partial R(p)}{\partial p} = \kappa_{\text{avg}} \hat{N} \mathbb{E}[\Phi]$. We now consider the case

$$p \geq \theta(\kappa_{\text{avg}} \Phi_{\text{max}}^{1-\theta})^{-1} \Leftrightarrow \Psi(p) \leq \Phi_{\text{max}}.$$

Then for $p \geq \theta(\kappa_{\text{avg}} \Phi_{\text{max}}^{1-\theta})^{-1}$,

$$B(p) = \hat{N} \kappa_{\text{avg}} \Psi(p) \left(1 - \frac{\Psi(p)^{1-\sigma}}{(2-\sigma)\Phi_{\text{max}}^{1-\sigma}} \right) > 0,$$

since $B(p) > 0$, $\text{sgn}(R'(p)) = \text{sgn}\left(\frac{R'(p)}{B(p)}\right)$. We will investigate $\text{sgn}(R'(p))$ by investigating $\text{sgn}\left(\frac{R'(p)}{B(p)}\right)$ and show that $\frac{\partial R(p)}{\partial p}$ has a unique solution \hat{p} of $\frac{\partial R(p)}{\partial p} = 0$ by showing that $\frac{R'(p)}{B(p)} = 0$ has a unique solution at \hat{p} . The first and second derivatives of $B(p)$ are,

$$\begin{aligned} \frac{\partial B(p)}{\partial p} &= \frac{-\hat{N} \kappa_{\text{avg}} \Psi(p)}{p(1-\theta)} \left(1 - \frac{\Psi(p)^{1-\sigma}}{\Phi_{\text{max}}^{1-\sigma}} \right), \\ \frac{\partial B(p)^2}{\partial^2 p} &= \frac{\hat{N} \kappa_{\text{avg}} \Psi(p)}{p^2(1-\theta)^2} \left((2-\theta) - \frac{(3-\sigma-\theta)\Psi(p)^{1-\sigma}}{\Phi_{\text{max}}^{1-\sigma}} \right). \end{aligned}$$

Let $B'(p) = \frac{\partial B(p)}{\partial p}$ and $B''(p) = \frac{\partial B(p)^2}{\partial^2 p}$. The first derivative of revenue function $R(p)$ is

$$\frac{\partial R(p)}{\partial p} = (p - \eta)B'(p) + B(p). \quad (18)$$

We have

$$\begin{aligned} \frac{\partial \left(\frac{R'(p)}{B(p)} \right)}{\partial p} &= \frac{B'(p)}{B(p)} + (p - \eta) \frac{B''(p)B(p) - B'(p)^2}{B(p)^2} \\ &= \frac{-l(p)}{p^2(1-\theta)^2 B(p)^2} < 0, \end{aligned}$$

where

$$\begin{aligned} l(p) &= (p - \eta) \left(\frac{(1-\sigma)^2 \Psi(p)^{1-\sigma}}{(2-\sigma)\Phi_{\text{max}}^{1-\sigma}} \right) + \\ &\quad \eta(1-\theta) \left(1 - \frac{\Psi(p)^{1-\sigma}}{\Phi_{\text{max}}^{1-\sigma}} \right) B(p) \\ &> 0. \end{aligned}$$

since $p \geq \eta$, $0 \leq \Psi(p) \leq \Phi_{\text{max}}$, $B(p) > 0$, and $\theta \in (0, 1)$. Thus, $\frac{R'(p)}{B(p)}$ is strictly decreasing in p . Note that $\frac{R'(\eta)}{B(\eta)} = 1 > 0$, and

$$\begin{aligned} \lim_{p \rightarrow \infty} \frac{R'(p)}{B(p)} &= 1 + \lim_{p \rightarrow \infty} \frac{-\frac{p-\eta}{p(1-\theta)} \left(1 - \frac{\Psi(p)^{1-\sigma}}{\Phi_{\text{max}}^{1-\sigma}} \right)}{1 - \frac{\Psi(p)^{1-\sigma}}{(2-\sigma)\Phi_{\text{max}}^{1-\sigma}}} \\ &= 1 - \frac{1}{1-\theta} < 0, \end{aligned}$$

since $\lim_{p \rightarrow \infty} \Psi(p) = 0$ and $\theta \in (0, 1)$. Therefore $\frac{R'(p)}{B(p)} < 0$ for sufficiently large p . Considering that $\frac{R'(p)}{B(p)}$ is a decreasing function of p and $\frac{R'(\eta)}{B(\eta)} > 0$, there should be a unique $\hat{p} \in (\eta, \infty)$ such that $\frac{R'(p)}{B(p)} = 0$ (note that $\hat{p} > \eta$). Since $B(p) > 0$

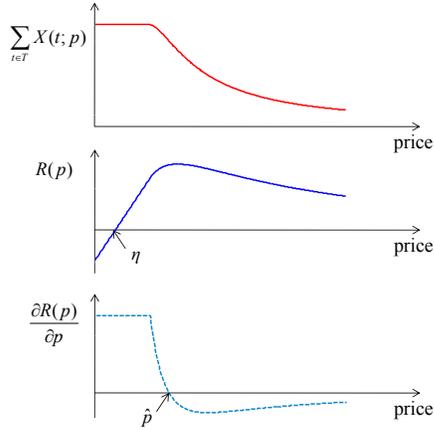


Fig. 13. An illustration of $\sum_{t \in T} X(t; p)$, $R(p)$, and $\frac{\partial R(p)}{\partial p}$ over volume price p .

for any p , $R'(p) = 0$ only at \hat{p} . Summarizing, the sign of $R'(p)$ is

$$\begin{aligned} \text{sgn}(R'(p)) &= \text{sgn}\left(\frac{R'(p)}{B(p)}\right) \\ &= \begin{cases} + & \text{if } \eta \leq p < \hat{p} \\ 0 & \text{if } p = \hat{p} \\ - & \text{if } p > \hat{p}. \end{cases} \end{aligned}$$

Thus, $R(p)$ is unimodal for $p > \eta$.

Step 2: Characterization of \mathcal{P} . We now find the set of feasible prices \mathcal{P} . Since $\sum_{t \in T} X(t) > 0$ and $\kappa_{\text{avg}} \leq 1$, the provider's revenue is negative if $p \leq \eta$ from (11). By the *provider rationality*, i.e., $R(p) > 0$ for $p \in \mathcal{P}$,

$$p \in \mathcal{P} \Rightarrow p > \eta. \quad (19)$$

$A(p)$ is nonincreasing in p , since

$$\frac{\partial A(p)}{\partial p} = \begin{cases} 0 & \text{if } \Psi(p) > \Phi_{\max} \\ \frac{-\hat{N}k\Psi(p)}{p(1-\theta)} \left(1 - \frac{\Psi(p)^{1-\sigma}}{\Phi_{\max}^{1-\sigma}}\right) & \text{if } \Psi(p) \leq \Phi_{\max} \end{cases}$$

Thus, if $p \in \mathcal{P}$, then

$$A(p) \leq C_{3g} \Leftrightarrow p \geq p_{\min},$$

where $p_{\min} = \inf\{p \mid A(p) \leq C_{3g}\}$. Note that $p_0 = \max\{p_{\min}, \eta\}$. Thus, if $\eta \geq p_{\min}$, $p_0 = \eta$ and $\mathcal{P} = (p_0, \infty)$, and if $\eta < p_{\min}$, $p_0 = p_{\min}$ and $\mathcal{P} = [p_0, \infty)$. Note that $p_{\min} = 0$ if and only if $\kappa_{\text{peak}} \hat{N} \mathbb{E}[\Phi] \leq C_{3g}$, since $A(0) = \kappa_{\text{peak}} \hat{N} \mathbb{E}[\Phi]$. From Steps 1 and 2, the result (i) holds.

Step 3: Proof of (ii). If $R'(p_0) \leq 0$, $\hat{p} \leq p_0$, $R(p_0) > 0$ and p_0 is the unique optimal price, since $R'(p) \leq 0$ for $p \in \mathcal{P}$. From $R(p_0) > 0$, $p_0 > \eta \geq 0$. Thus, $A(p_0) = C_{3g}$ and the network is *opt-saturated*.

We now show that $\frac{\partial p_0(\kappa_{\text{avg}})}{\partial \kappa_{\text{avg}}} > 0$. To study the impact of κ_{peak} , we regard κ_{peak} as a variable, not a constant. Recall that $p^* = p_0$ and $A(p_0) = C_{3g}$ if the network is *opt-saturated*. From (4),

$$\kappa_{\text{peak}} = \frac{C_{3g}}{\sum_{t \in T} X(t; p_0)}, \quad (20)$$

where $X(t; p)$ is the total traffic arrival at time t when price is p . We denote $V(p) = \sum_{t \in T} X(t; p)$. Differentiating by κ_{peak} , we yield

$$\frac{\partial p_0}{\partial \kappa_{\text{peak}}} = \frac{-V(p_0)^2}{C_{3g} V'(p_0)} > 0, \quad (21)$$

where

$$\frac{\partial V(p)}{\partial p} = \begin{cases} 0 & \text{if } \Psi(p) > \Phi_{\max} \\ \frac{-\hat{N}\Psi(p)}{p(1-\theta)} \left(1 - \frac{\Psi(p)^{1-\sigma}}{\Phi_{\max}^{1-\sigma}}\right) & \text{if } \Psi(p) \leq \Phi_{\max} \end{cases}$$

since $V(p) > 0$ and $V'(p) < 0$, for $p \in \mathcal{P}$ in *opt-saturated* case. Note that $V'(p) = 0$ only if $\kappa_{\text{peak}} V(p) = \kappa_{\text{peak}} \hat{N} \mathbb{E}[\Phi] > C_{3g}$ and $\kappa_{\text{peak}} V(p) \leq C_{3g}$ over \mathcal{P} in *opt-saturated* case. By (21), the optimal price p^* decreases and actual payment per unit traffic $p^* \kappa_{\text{avg}}$ decreases as κ_{peak} decreases. We have proven (ii) holds.

Step 4: Proof of (iii). We now consider the case $R'(p_0) > 0$. If $\eta \geq p_{\min}$, then $\mathcal{P} = (\eta, \infty)$ and $\hat{p} > \eta$. Thus, \hat{p} is the unique optimal price. To show that $A(\hat{p}) < C_{3g}$, we consider two cases $p_{\min} = 0$ and $p_{\min} > 0$. Recall that $p_{\min} = 0$ if and only if $\kappa_{\text{peak}} \hat{N} \mathbb{E}[\Phi] \leq C_{3g}$, since $A(0) = \kappa_{\text{peak}} \hat{N} \mathbb{E}[\Phi]$. Thus, if $p_{\min} = 0$, $A(p_{\min}) = \kappa_{\text{peak}} \hat{N} \mathbb{E}[\Phi] \leq C_{3g}$. Note that $A'(p) < 0$ for p such that $\Psi(p) \leq \Phi_{\max}$, i.e., $p \geq \theta(\kappa_{\text{avg}} \Phi_{\max}^{1-\theta})$. Since $\hat{p} \geq \theta(\kappa_{\text{avg}} \Phi_{\max}^{1-\theta})$, $A'(\hat{p}) < 0$ and $A(\hat{p}) < A(p_{\min}) \leq C_{3g}$. If $p_{\min} > 0$, $A(p_{\min}) = C_{3g} < \kappa_{\text{peak}} \hat{N} \mathbb{E}[\Phi]$. Since $A'(\hat{p}) < 0$, $A(\hat{p}) < A(p_0) \leq C_{3g}$. The network is *opt-unsaturated*. If $\eta < p_{\min}$, then $p_0 = p_{\min}$, $\mathcal{P} = [p_{\min}, \infty)$ and $p_{\min} > 0$. Note that $A(p_{\min}) = C_{3g}$ if $p_{\min} > 0$. Recall that if $R'(p_0) > 0$, then $\hat{p} > p_0$ and \hat{p} is the unique optimal price. Since $A(\hat{p}) < A(p_{\min}) = C_{3g}$ (see Fig. 13), the network is *opt-unsaturated*.

We now show that $\frac{\partial(\hat{p}(\kappa_{\text{avg}})\kappa_{\text{avg}})}{\partial \kappa_{\text{avg}}} > 0$ so that the optimal per-traffic payment is reduced as κ_{avg} decreases. We use $\hat{p}(\kappa_{\text{avg}})$ to emphasize the impact of κ_{avg} . From (18) and the condition $R'(\hat{p}(\kappa_{\text{avg}})) = 0$,

$$\begin{aligned} \hat{p}(\kappa_{\text{avg}}) - \eta &= -\frac{B(\hat{p})}{B'(\hat{p})} \\ &= \frac{\hat{p}(1-\theta) \left(1 - \frac{h(\kappa_{\text{avg}})}{2-\sigma}\right)}{1 - h(\kappa_{\text{avg}})}, \end{aligned}$$

where $h(\kappa_{\text{avg}}) = \frac{\left(\frac{\theta}{\hat{p}(\kappa_{\text{avg}})\kappa_{\text{avg}}}\right)^{\frac{1-\sigma}{\sigma}}}{\Phi_{\max}^{1-\sigma}} > 0$. Differentiating by \hat{p} and rearranging it, the derivative $\frac{\partial \hat{p}}{\partial \kappa_{\text{avg}}}$ is as follows:

$$\frac{\partial \hat{p}}{\partial \kappa_{\text{avg}}} = -\frac{\hat{p}}{\kappa_{\text{avg}}} \frac{(1-\sigma)^2 h(\kappa_{\text{avg}})}{L(\kappa_{\text{avg}}) + (1-\sigma)^2 h(\kappa_{\text{avg}})},$$

where $L(\kappa_{\text{avg}}) = (1-h(\kappa_{\text{avg}}))(\theta(2-\sigma) - h(\kappa_{\text{avg}})(1+\theta-\sigma))$. Thus, the derivative of payment per unit traffic is,

$$\begin{aligned} \frac{\partial(\hat{p}(\kappa_{\text{avg}})\kappa_{\text{avg}})}{\partial \kappa_{\text{avg}}} &= \hat{p} + \kappa_{\text{avg}} \frac{\partial \hat{p}}{\partial \kappa_{\text{avg}}} \\ &= \hat{p} \left(\frac{L(\kappa_{\text{avg}})}{L(\kappa_{\text{avg}}) + (1-\sigma)^2 h(\kappa_{\text{avg}})} \right). \end{aligned}$$

We want to show that $\frac{\partial(\hat{p}(\kappa_{\text{avg}})\kappa_{\text{avg}})}{\partial \kappa_{\text{avg}}} > 0$. From the condition $R'(\hat{p}(\kappa_{\text{avg}})) = 0$, we have

$$\frac{1 - \frac{h(\kappa_{\text{avg}})}{2-\sigma}}{1 - h(\kappa_{\text{avg}})} = \frac{p - \eta}{p(1-\theta)} \leq \frac{1}{1-\theta},$$

since $\hat{p} \geq \eta$, $\eta \geq 0$ and $\theta \in (0, 1)$. Thus, $h(\kappa_{\text{avg}}) \leq \frac{\theta(2-\sigma)}{3-\sigma-\theta}$. Applying this condition to $L(\kappa_{\text{avg}})$, we have $L(\kappa_{\text{avg}}) > 0$ and therefore,

$$\frac{\partial \hat{p}(\kappa_{\text{avg}})}{\partial \kappa_{\text{avg}}} < 0 \quad \text{and} \quad \frac{\partial(\hat{p}(\kappa_{\text{avg}})\kappa_{\text{avg}})}{\partial \kappa_{\text{avg}}} > 0.$$

Note that actual payment per unit traffic $\hat{p}(\kappa_{\text{avg}})\kappa_{\text{avg}}$ is increasing as κ_{avg} decreases. We have proven (iii) holds. ■

D. Proof of Theorem 4.2

(i) *Opt-saturated.* Recall that the net-utility of a subscriber with Φ is

$$\sum_{t \in T} w(t)^{1-\theta} x_{\Phi}^*(t)^{\theta} - p\kappa_{\text{avg}} \sum_{t \in T} x_{\Phi}^*(t)$$

where

$$x_{\Phi}^*(t) = \min \left\{ \phi(t), w(t) \left(\frac{\theta}{p\kappa_{\text{avg}}} \right)^{\frac{1}{1-\theta}} \right\},$$

and $\Phi = \sum_{t \in T} \phi(t)$. Therefore the net utility of a user is given by

$$U_{\Phi}(x_{\Phi}^*) = \begin{cases} \Phi^{\theta} - p\kappa_{\text{avg}}\Phi & \text{if } \Phi < \left(\frac{\theta}{p\kappa_{\text{avg}}} \right)^{\frac{1}{1-\theta}} \\ \left(1 - \theta \frac{1}{1-\theta} \right) \left(\frac{\theta}{p\kappa_{\text{avg}}} \right)^{\frac{\theta}{1-\theta}} & \text{if } \Phi > \left(\frac{\theta}{p\kappa_{\text{avg}}} \right)^{\frac{1}{1-\theta}} \end{cases}.$$

It is clear that the net-utility of a user increases as p decreases.

Consider the revenue function at the optimal price p^* ; $R(p^*)$. When a network is opt-saturated, by Proposition 4.2(ii), $p^* = p_0$ such that $A(p_0) = C_{3g}$. From (20), p^* is dependent of κ_{peak} . To show that $R(p^*)$ increases as κ_{peak} decreases, we will show that $\frac{\partial R(p^*)}{\partial \kappa_{\text{peak}}} < 0$. The first derivative of $R(p^*)$ with respect to κ_{peak} is,

$$\frac{\partial R(p^*)}{\partial \kappa_{\text{peak}}} = \frac{\partial R(p^*)}{\partial p^*} \frac{\partial p^*}{\partial \kappa_{\text{peak}}}.$$

From (21), p^* is an increasing function of κ_{peak} . Therefore, it is enough to show that $\frac{\partial R(p^*)}{\partial p^*} < 0$. We have already proven that $\frac{\partial R(p^*)}{\partial p^*} < 0$ over \mathcal{P} for an opt-saturated network in the proof of Proposition 4.2(ii).

(ii) *Opt-unsaturated.* By the same argument of Theorem 4.2(i), net utility of a user and user surplus are increasing as κ_{avg} decreases.

We now show that revenue is increasing as κ_{avg} decreases. We will use $R(p, \kappa_{\text{avg}})$, $Y(t; p, \kappa_{\text{avg}})$ and $\mathcal{P}(\kappa_{\text{avg}})$ to emphasize the impact of κ_{avg} . Suppose that κ_{avg} is decreased by a factor of $\rho < 1$. i.e., $\kappa_{\text{avg}}^{\text{new}} = \rho\kappa_{\text{avg}}$. Let $p^{\text{new}} := \frac{p}{\rho}$. If we show that

$$\forall p \in \mathcal{P}(\kappa_{\text{avg}}) \Rightarrow p^{\text{new}} \in \mathcal{P}(\kappa_{\text{avg}}^{\text{new}})$$

and $R(p^{\text{new}}, \kappa_{\text{avg}}^{\text{new}}) > R(p, \kappa_{\text{avg}})$ hold, then

$$R(p^*, \kappa_{\text{avg}}) < R\left(\frac{p^*}{\rho}, \kappa_{\text{avg}}^{\text{new}}\right) \leq \max_{p \in \mathcal{P}(\kappa_{\text{avg}}^{\text{new}})} R(p, \kappa_{\text{avg}}^{\text{new}})$$

where p^* is the optimal price with $\kappa_{\text{avg}}^{\text{new}}$ which implies that the maximum revenue is increasing as κ_{avg} is decreasing.

We show that $p^{\text{new}} \in \mathcal{P}(\kappa_{\text{avg}}^{\text{new}})$; $R(p^{\text{new}}, \kappa_{\text{avg}}^{\text{new}}) > 0$ and $\max_{t \in T} Y(t; p^{\text{new}}, \kappa_{\text{avg}}^{\text{new}}) \leq C_{3g}$. By (16), it is obvious that

$$U_{p, \kappa_{\text{avg}}}(x) = U_{p^{\text{new}}, \kappa_{\text{avg}}^{\text{new}}}(x).$$

Since the user optimization problems are identical, the total traffics are the same, $\mathbf{x}^{\text{new}} = \mathbf{x}^*$. Then the corresponding 3G traffic \mathbf{y}^{new} and \mathbf{y} satisfy

$$\sum_{t \in T} y^{\text{new}} = \kappa_{\text{avg}}^{\text{new}} \sum_{t \in T} x^*(t) = \rho \sum_{t \in T} y(t) < \sum_{t \in T} y(t).$$

Therefore

$$\begin{aligned} \sum_{t \in T} Y(t; p^{\text{new}}, \kappa_{\text{avg}}^{\text{new}}) &= \rho \sum_{t \in T} Y(t; p, \kappa_{\text{avg}}) \quad (22) \\ &< \sum_{t \in T} Y(t; p, \kappa_{\text{avg}}), \end{aligned}$$

Consider the corresponding revenue function $R(p, \kappa_{\text{avg}})$ and $R(p^{\text{new}}, \kappa_{\text{avg}}^{\text{new}})$.

$$\begin{aligned} R(p^{\text{new}}, \kappa_{\text{avg}}^{\text{new}}) &= \left(\frac{p}{\rho} - \eta \right) \sum_{t \in T} Y(t; p^{\text{new}}, \kappa_{\text{avg}}^{\text{new}}) \\ &= (p - \rho\eta) \sum_{t \in T} Y(t; p, \kappa_{\text{avg}}) \quad (\because (22)) \\ &> R(p, \kappa_{\text{avg}}) \quad (\because p \in \mathcal{P}(\kappa_{\text{avg}})), \end{aligned}$$

where $R(p, \kappa_{\text{avg}}) = (p - \eta) \sum_{t \in T} Y(t; p, \kappa_{\text{avg}})$. Now we have shown that $R(p^{\text{new}}, \kappa_{\text{avg}}^{\text{new}}) > R(p, \kappa_{\text{avg}}) > 0$. Hence $\rho^{-1}p \in \mathcal{P}(\kappa_{\text{avg}}^{\text{new}})$. ■

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