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摘　　要

随着无线通信技术的不断发展，无线应用逐渐进入生产生活中的各个领域。人们对无线通信系统的性能需求也逐渐提升，这主要包括更高的通信带宽、更低的通信时延、更稳定的通信连接、更大规模的通信容量以及更高的通信效率。然而，现有的无线通信系统难以达到以上要求，人们迫切盼望着下一代无线通信系统的到来。

毫米波通信因其丰富的频谱资源，普遍被认为将在下一代无线通信系统中发挥巨大作用。然而毫米波信号在空间下中衰减很快，需要利用大规模多输入多输出天线阵列通过波束成形技术将信号集中成极窄的方向性波束进行传输，波束越窄，能量传输效率、频谱利用率与系统容量等性能就越高。新的技术带来了丰富的计算与通信资源，也同时为资源的优化分配带来了新的挑战，如何在资源有限的情况下尽可能地提高系统各项性能便成为了毫米波通信中亟需解决的问题。本文在综述国内外最新研究成果的基础上，研究了多种场景下毫米波无线通信中的资源优化问题，并分别提出了对应的优化算法，为毫米波通信的实际应用提供了可行的方案。本文的主要工作如下:

1. 概述了毫米波无线通信领域的研究背景与应用，并综述相关资源优化问题研究进展。

2. 研究了在毫米波无线通信系统中多用户快速定位与跟踪问题。毫米波通信需要发射与接收双方通过波束对准，利用极窄的波束建立连接。例如在蜂窝小区场景中，基站需要对多个用户位置信息进行实时准确的估计与跟踪，以建立低时延的毫米波方向性通信。现有的多目标跟踪算法，如概率假设密度粒子滤波算法，难以做到流水线化计算，制约了跟踪实时性的进一步提高。对此，本文提出了一种改进的重采样算法，通过引入粒子复制序列集合以及待复制粒子序列，使得需要重采样的粒子在只获得自身信息与之前重采样粒子信息时即可进行粒子复制运算。通过引入该改进的重采样算法，整个概率假设密度粒子滤波算法能够实现完全流水线化运算。在此基础上，为进一步降低运行时延，在多核处理器硬件平台上提出了计算资源优化分配问题，并通过解决一组混合整数规划问题，得到了高时效的近似解法。仿真结果验证了提出算法在保证跟踪精度的情况下，能显著降低整个滤波算法的计算时延，有效提高多用户跟踪的实

时性，为毫米波通信的建立奠定了基础，并为基站与每个用户的低时延通信提供了保证。

3. 研究了毫米波通信应用在蜂窝小区网络中的基站资源优化分配问题。考虑基站引入大规模多输入多输出天线阵列，当已知小区内多个用户位置的情况下，如何分配其天线资源以最大化系统收益即系统吞吐量的问题。将基站上的大规模天线阵列虚拟地分成若干个均匀线性子阵列，分别通过波束成形技术与对应的用户进行通信。由于大规模天线阵列与每个均匀线性子阵列都有着固定的形状，因此本文将资源优化问题建模为如何在矩形阵列中设计并合理地放置这些子阵列使得系统的收益最大。这既需要考虑每个用户对应子阵列的天线数量，又需要考虑子阵列在矩形阵列中的位置。根据子阵列的放置方式不同又包含两种的情况，1）所有线性子阵列都平行于矩形阵列的一条边；2）为了进一步提高系统收益，线性子阵列可以相互垂直放置。本文对以上两种情况分别建模，解决了两个 NP-hard 问题，得到了两种情况下多项式时间的近似算法。仿真结果验证了提出的两种算法在不同情况下都能有效地分配天线资源，得到有性能保证的系统收益。

4. 研究了毫米波通信应用在无线数据中心网络中的资源优化分配问题。考虑在数据中心网络中利用毫米波无线连接代替传统服务器间的有线连接，以提高数据中心网络灵活性及可扩展性的问题。随着数据应用不断的发展，数据中心网络中涌现了极度不平衡流量。为了降低不平衡流量带来的网络拥堵，在每个服务器机架顶布置毫米波阵列天线以建立点对点无线数据中心网络。通过分析阵列天线与波束成形技术特点，本文提出了无线数据中心网络硬件实现方式以及单层和三层两种网络拓扑结构，并给出了网络拓扑中节点与边的生成方式。之后，为了降低给定时间内系统中任务流的最大完成时间，本文建模了天线资源分配优化问题，通过变量替换等方式将其转化为几何规划问题并给出了解法。仿真结果验证了提出的毫米波无线数据中心网络结构与资源优化算法的有效性。

5. 对全文进行了总结，并对进一步的研究工作进行了展望。

关键词：毫米波通信；大规模多输入多输出；资源优化；数据中心网络

Abstract

With the rapid development of the wireless communication technologies, abundant of wireless applications have been implemented in our daily life. Meanwhile, the higher performances are in urgent demands, including the higher bandwidth, the lower latency, wider coverage and massive capacity and connections. The state-of-the-art system can not provide the requested performance, people are waiting for the next generation communication systems.

In the next generation communication systems, one of the most promising technologies is the millimeter wave(mmWave) wireless communication. Millimeter wave occupies luxuriant undeveloped spectrum resources, which could provide super wide bandwidth. However,due to the extreme high frequency, the mmWave attenuates quite fast in the free space. Hereby the Massive MIMO system engages to transmit the mmWave with directional narrow beam to concentrate the energy. The narrower the beam width, the higher energy efficiency, spectrum efficiency and system performance will be achieved. New technologies bring not only abundant resources, but also grand challenges in resource allocation problems. Then it is an urgent and primal problem that how to manage and utilize the limited resources to optimize the network performance such as the real-time performance and system throughput. Based on the latest observation and results, this dissertation investigates the resource management and optimization problem under specific scenarios and provides the corresponding solutions, which may help the design of the next generation wireless communication systems. The main contributions are summarized as follows:

1. A brief review on the background, overview, main characteristics, applications and related works about resource management and optimization for mmWave wireless communications is provided.

2. Research on the fast positioning and tracking problem in the mmWave wireless communication system. mmWave wireless communications require the beam alignment of the transmitter and the receiver to build the narrow beam link. Then, in the mobile network scenario,

the base station need the accurate positioning and tracking information of multiple users to establish and maintain the communication timely. Nevertheless the state-of-the-art multiple target tracking algorithms can not provide efficient procedure to further increase the real-time performance. We thereby introduce an improved resampling algorithm to ensure the particles in the particle PHD filter operate in a pipeline way without waiting for other particles' information. Based on the algorithm, we optimize the computational resource in the multi-core processor platform to reduce the operating time delay by solving a mixed integer programming problem. The simulation results demonstrate the time efficiency of our algorithm with the competitive tracking performance.

3. Research on the resource allocation problem in the massive MIMO mmWave cellular communication system. The target is to optimize the system performance by properly allocating the antenna resources. The antenna array on the base station is virtually divided into several sub-arrays, each sub-array communicates with one user. The problem lies in how to arrange the sub-arrays to maximize the system throughput. Not only the number of antennas in each sub-array, but also their relative positions need to be optimized. Two scenarios are considered in this problem, includes the one-direction scenario and the orthogonal direction scenario. Both problems are NP-hard. Therfore, the approximation algorithms are proposed, together with the computational complexities and the lower bounds. The simulation results demonstrate the algorithms can achieve good performance in both scenarios.

4. Research on the system establishment and resource allocation problem in the mmWave wireless data center network (DCN). By introducing the 60GHz wireless link, the bandwidth, reconfigurability and the scalability are strongly improved in DCN. Under the phenomenon of unbalanced data flow, the communication hot spots appear in the DCNs which undermine the system performance. By setting the mmWave antenna arrays on each ToR, We build both one-tier and 3-tier wireless DCN constructions and topologies. We also optimize the antenna allocation problems for the antenna arrays on each ToRs, by transforming the problem into a geometric programming problem. The simulation results demonstrate the efficiency of our system and the allocation algorithms.

5. The conclusions are drawn with future work at the end of the dissertation.

Keywords: mmWave; Massive MIMO; Resource Allocation; Data Center Network

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1 毫米波通信系统中多用户快速跟踪问题研究

本章摘要： Mobile social networks have greatly strengthened people's online social interactions, generating massive volume of mobile data traffic, and bringing remarkable revenues to the wireless service providers. Meanwhile, the potential revenue growth is restrained by the network capacity of physical communication infrastructure, and also challenged by the competition among service providers themselves. In this paper, we study the pricing strategies of multiple service providers in a competitive data service market, where mobile users' data consumption behaviors are influenced by two effects: the positive network effect and the congestion effect. To analyze the strategic interactions between mobile users and service providers, we device a two-stage Stackelberg game consisting a pricing game in Stage I and a usage game in Stage II, respectively. In particular, for the usage game, we characterize the equilibrium solution and establish its uniqueness. For the pricing game, our analysis indicates that a mixed-strategy equilibrium solution is guaranteed for the scenario with rational providers as well as the scenario with providers of bounded rationality. We further develop a distributed learning algorithm for finding a mixed-strategy equilibrium solution in the second scenario. Our numerical results provide insights into how positive network effect and congestion effect would impact the system performance, and demonstrate that the bounded rational behavior incurs degradation to service providers' revenues.

关键词：移动社交网络；网络定价；网络效应；博弈论；期望理论

1.1 引言

use of smart devices has experienced immense growth in the past decade, becoming an indispensable part of the daily life for most people around world, regardless of their backgrounds and age. In line with the pervasive penetration of smart devices, recent years have also witnessed the spectacular success of online social networks (e.g., Facebook[1], Twitter[2]), which have greatly strengthened people's online social interactions. Attributed to the proliferation of both smart devices and online social networks, the mobile social users has increased by 30% year-over-year to surpass 2.5 billion globally in January 2017, accounting for 91% of the total social media users[3].

The explosion of mobile social users not only brings remarkable profit to the social network platforms, but also delivers great revenues to the wireless service providers. Intuitively, mobile social applications are well-designed nowadays to encourage people's online interaction with either their known friends or other unacquainted users anytime and anywhere (e.g., via messaging, media sharing, and online gaming, etc.). The strengthened and expanded social relationship will in turn give rise to greater data consumption owing to *positive network effect*[1][4]. For instance, a user usually becomes more involved into playing a mobile game if that game has gained much popularity among her social friends. A psychological explanation of this effect is that users always want to be perceived as part of their peers. Such kind of positive network effect could be conveyed extensively throughout the mobile social network, resulting a fire-up of data consumption that has potential to generate significant revenues for the wireless providers.

However, with increasingly many on-the-shelf mobile applications being data-hungry, the potential growth of providers' revenues from network effect is constrained by the capacity of wireless communication network. Take the online mobile game platform as an example, the increasing number of active users at the peak time and the generated accumulated data traffic will result in serious congestion (hence service delays) due to limited bandwidth. And the resulted bad user experience would discourage users' data usage in such kind of delay-sensitive applications, which brings revenue loss to service providers.

Recently, the authors in[5] have investigated the mobile users' data consumption behavior under both the network effect and the congestion effect in a single wireless service provider market. Meanwhile, instead of being restricted to a single service provider, mobile users nowadays have had the option to purchase services from multiple wireless service providers[2]. Motivated by this observation, this study considers a scenario where multiple service providers need to compete strategically for the shares of the wireless service market to maximize their business revenues. Another observation inspiring this study is that individuals' decision making in reality usually deviate from the rational ones expected according to the well-established Expected Utility Theory framework[7].

[1] The network effect is a concept in economic and business describing that the value of a good or service to one user is influenced by others' valuation on that good or service. A positive network effect normally refers to the phenomenon whereby a product or service becomes more valuable as more people accept it, encouraging ever-increasing numbers of users.

[2] For example, mobile users can subscribe to the service of both T-mobile and Sprint via virtual network operator such as Google's Project Fi[6].

Some existing research works done within the field of behavior economics[8] have indicated that the irrationality is attributed to the fact that different individuals would have different and subjective evaluations on their risks and revenues when facing with competitions and uncertainties in practice. With all these insights, it is of great interest to study the pricing-usage decision interaction in an oligopoly market of multiple wireless service providers.

In a nut shell, this paper studies a wireless service market with multiple competitive service providers, and a group of data consuming mobile users that strategically determine their data usage subject to the two different effects, namely positive network effect and congestion effect. To this end, we formulate the pricing-usage problem as a *Stackelberg game*[9], in which service providers and individual users determine their strategies aiming to get to an equilibrium state, where no one could be better off by unilaterally deviate from the equilibrium point. One key challenge in characterizing the game lies in the high dimensionality of each user's strategy space. To tackle this challenge, we treat each link connecting one user and one provider as a "virtual user", and quantify the data usage of each "virtual user" accordingly. Specifically, in Stage I of the game, providers deliberately set the unit price of their data service in order to maximize her potential revenue. In Stage II, each "virtual user" determines her data usage strategically to optimize the corresponding payoff, given the service price of each provider. Under some technical conditions, we show both the existence and uniqueness of the equilibrium solution among "virtual users", based on which, we further show the existence of an ϵ-mixed-strategy pricing equilibrium for the providers.

In order to characterize the pricing behaviors of bounded rational providers, we further study the pricing game in Stage II by appealing to *Prospect Theory*[10]. This Nobel-prize-winning theory has been utilized in several real-life applications to model and explain individuals' decisions under risks and uncertainty[11,12]. In this study, we particularly consider two main aspects of Prospect Theory: the *probability distortion effect* and the *utility framing effect*. We show that the existence of an ϵ-mixed-strategy pricing equilibrium still holds under the two effects given a mild condition. Since service providers' payoffs are no longer public information, we resort to a distributed learning algorithm, by which service providers with partial observation can learn to play out an ϵ-mixed-strategy pricing equilibrium. Through numerical results, we show that the expected revenue of provider suffers from a degradation as a result of providers' bounded rational behaviors.

The remainder of the paper is organized as follows. We first discuss the related work in Section 1.2. In Section 3.3, we describe the basic formulation of the two-stage Stackelberg game between wireless service providers and mobile users. In Section 1.4, we study the usage game among mobile users and characterize the link demand equilibrium of the game. Then we study the pricing game among providers in Section 1.5, followed by the Section 1.6 which revisits the pricing game by appealing to Prospect Theory. Numerical results are given in Section 1.7, and Section 3.7 concludes the paper.

1.2 研究现状

In communication networks, congestion occurs as traffic load increases beyond the capacity determined by the physical nature of the infrastructure. The impact of congestion effect might not be prominence in some low-data-rate communication schemes (e.g.,[13] and[14]). While it is much more significant in many high-data-rate communication systems and has been studied extensively in related literatures (see, e.g.[15–17] and the references therein).

In recent years, the social aspect of mobile networking has attracted much attention of service providers and also platform developers. As more and more mobile users are nowadays connected by online social networks (e.g., Facebook[1], Twitter[2]), both the influences and information of users can propagate within the crowds faster than ever[18]. In[4], the social effect among users has been modeled as a kind of positive network effect. In[19], similar idea was adopted to characterize the effect that growing population of socially connected users in crowdsourcing system results in more intrinsic rewards, which helps save a part of extrinsic rewards that are supposed to be provided by the platform. In[20], in order to reduce the peak cellular load, the authors proposed a family of algorithms that proactively push content to particular users that are selected based on their positions in the social network.

Along another line of literatures, social influences among individuals have been utilized in solving many network design and optimization problems. In[21], Chen *et al.* have leveraged social trust and social reciprocity to enhance cooperative D2D communication by casting the problem to a coalitional game. In[22], the social distances between user equipments were exploited for the user association to enhance the system performance of a small cell network with underlaid D2D communication. In[23], Yang *et al.* proposed a mobile crowd sensing system design that leverages social ties among mobile users to incentivize their participation and global cooperation for higher payoffs. In[24], the authors developed a social group utility maximization (SGUM) framework, in which each user cares about the “group utility” consisting of her own utility as well as her social friends’ utilities.

The pricing problem in communication networks has been addressed extensively in the literature[25–29]. There has been a line of works focusing on investigating the pricing strategies of a single service provider, with the mobile users' data usage behavior subject to positive network effect (see, e.g.,[30–32]). To the best of our knowledge, very little works on network pricing have considered the impact of both network effect and congestion effect. The authors in[5] first studied the pricing strategy of a single service provider in a monopoly market where mobile users' data usage behaviors are subject to both the two effects. In contrast to[5], our preliminary work[33] investigated the pricing problem in an oligopoly market setting, where multiple service providers compete against each other for mobile users' data consumption.

Recently, Prospect Theory[10] has been employed to model the decision making process within wireless networks in practice. In[11], Li *et al.* studied a wireless random access game, where users strategically determine their transmission probabilities over a collision channel under the probability distortion effect of Prospect Theory. Yu *et al.* in[12] studied a data market model, where users need to choose to be a data seller or a data buyer, and also determine the amount of data being traded. They formulated the problem as a non-convex optimization problem considering both the probability distortion effect and the utility framing effect on users' decision behaviors.

In this paper, we extend our discussion in preliminary work[33] to a broader scope by considering the case where service providers can be of bounded rationality. And in this more general setting, we show the existence of a mixed-strategy pricing equilibrium of a usage game, and establish the condition under which the equilibrium is unique. Our numerical result indicates that service providers' bounded rationality can lead to degradation on the total revenues. While part of this work has been presented in[33], complete proofs for the main results have been added in this paper to facilitate readers' better understanding.

1.3 Pricing Competition with Socially-aware Mobile Data Consumption

In this section, we first provide the oligopoly market model for the wireless data service, in which a crowd of socially connected mobile users can purchase and consume the data service from a group of service providers. We next describe the two-stage *Stackelberg game* formulation that models the interactions between providers and users.

1.3.1 System Model

Consider a set of mobile users $\mathcal{N} \triangleq \{1, \cdots, N\}$ consuming perfectly substitutable wireless services[3] from a set of wireless service providers $\mathcal{K} \triangleq \{1, 2, \cdots, K\}$. Each user can subscribe to more than one service providers with the data consumed by user i from service provider k denoted by x_i^k. We let $\mathbf{X} \in \mathbb{R}^{N\times K}$ denotes the usage profile of all the users, and $\mathbf{X}_{-i}$ denotes the joint usage profile without user i.

The mobile users are assumed to be socially connected, with the social impact of user j on user i quantified by a positive social tie $g_{ij} \in [0, 1]$. The social impact induces *positive network effect*, under which mobile users are inclined to experience more utility gain as the usages of their social friends increase.

As data consumption increases, the congestion effect (e.g., service delays) will become prominent, and need to be explicitly considered in our model. To this end, the individual utility of each mobile user includes four parts: the intrinsic utility, the data usage cost, the network effect, and the congestion effect. Specifically, given the unit service price charged by each provider, the individual utility of user i can be written as

$$
\begin{aligned}
u_i(\mathbf{x}_i, \mathbf{X}_{-i}, \mathbf{p}) = & \underbrace{a_i \sum_{k\in\mathcal{K}} x_i^k - \frac{1}{2} b_i (\sum_{k\in\mathcal{K}} x_i^k)^2}_{\text{Intrinsic Utility}} - \underbrace{\sum_{k\in\mathcal{K}} p_k x_i^k}_{\text{Data Usage Cost}} \\
& + \underbrace{\sum_{k\in\mathcal{K}} x_i^k \sum_{j\in\mathcal{N}} g_{ij} \sum_{m\in\mathcal{K}} x_j^m}_{\text{Network Effect}} - \underbrace{\frac{c}{2} \sum_{k\in\mathcal{K}, x_i^k>0} (\sum_{j\in\mathcal{N}} x_j^k)^2}_{\text{Congestion Effect}},
\end{aligned}
\tag{1-1}
$$

where $\mathbf{x}_i = (x_i^1, x_i^2, \cdots, x_i^K)$ denotes the usage profile of user i, and $\mathbf{p} = (p_1, \cdots, p_K)$ denotes the joint pricing profile of all the service providers where p_k denoting the unit price of data service from provider $k \in \mathcal{K}$. Following[5] and[31], we apply a quadratic form intrinsic utility function, which serves as a good second-order approximation for a broad class of concave utility functions. Specifically, $a_i > 0$ and $b_i > 0$ are two intrinsic coefficients that characterize user i's intrinsic valuation of her data consumption. The network effect is modeled as a linear function of the total data demand from user i, so that her marginal utility depends on the aggregated data demand of her social friends weighted by the social tie weights (i.e., $\sum_{j\in\mathcal{N}} g_{ij} \sum_{m\in\mathcal{K}} x_j^m$). The congestion effect a user experiences from a single service provider is proportional to the square of total data traffic

[3] Perfectly substitutable wireless services here means that the same amount of data usage from different service providers has the same valuation to a mobile user.

of that service provider, with parameter $c > 0$ models the condition of the physical communication medium. The total congestion effect a user experiences is the aggregated congestion effect from all service providers that she has connection with.

For each service provider $k \in \mathcal{K}$, we denote q_k as her customized unit service cost, and model her revenue v_k as the the total payment she received minus the total service cost she incurred,

$$v_k = p_k \sum_{j \in \mathcal{N}} x_j^k - q_k \sum_{j \in \mathcal{N}} x_j^k, \quad \forall k \in \mathcal{K}, \tag{1-2}$$

where p_k is determined by provider k by choosing a value from her price space $\mathcal{P}_k \triangleq \{p_k^1, p_k^2, \cdots, p_k^{M_k}\}$, which consists of M_k different price levels. The joint price space of all service providers is defined as $\mathcal{P} \triangleq \prod_{k \in \mathcal{K}} \mathcal{P}_k$. Fig. 3-2 illustrates the system model and the interactions among service providers and mobile users. Basically, the service providers compete for data demanding mobile users by strategically pricing their services; given the pricing profiles, the self-interested mobile users need to decide their data usage profile under the impacts of network effect and congestion effect. In the next section, we introduce the game theoretic formulation of the problem.

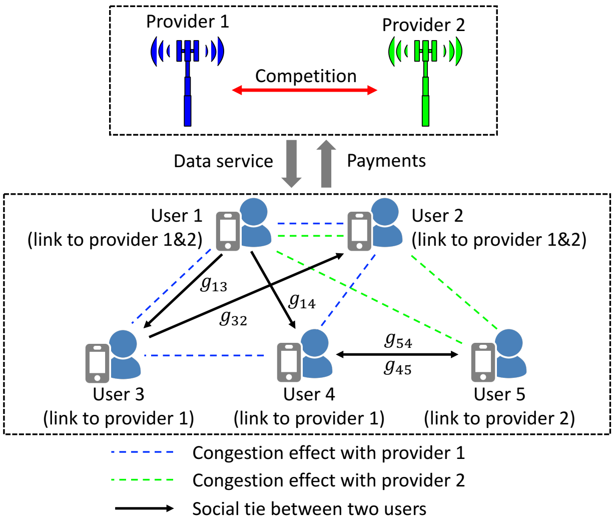

图 1-1　An illustration of the system model and interactions among service providers and mobile users.

1.3.2　Pricing-usage Game Formulation

In this section, we cast the pricing-usage problem as a two-stage *Stackelberg game* where service providers determine their pricing profiles via a non-cooperative game in stage I, based on the total data demands determined by mobile users via a subgame in stage II. Different from the monopoly market considered in[5], the strategy space of each mobile user in our case is multidimensional, making it more challenging to characterize the equilibrium of the usage game. To tackle this challenge, we treat the link connecting a mobile user and a provider as a *virtual player*, and cast the data usage problem among users as a non-cooperative game played by virtual players (links). Let $\mathcal{L} \triangleq \{(i,k)\}_{i\in\mathcal{N},k\in\mathcal{K}}$ denote the set of $L = N \times K$ user-provider links. The pure strategy of virtual player (i,k) is the data usage x_i^k over the link (i,k) with its payoff corresponds to u_i (i.e., the links starting from the same user have the same payoff). And it follows that the social network effect that link (i',k') has on link (i,k) can be characterized by the social tie $g_{ii'}$ between user i and i'. We denote $\mathbf{x} = (\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_K)$ as the joint link usage profile of all links, and use $\mathbf{x}_{-(i,k)}$ to denote the joint usage profile excluding (i,k). And the two-stage game can be formally defined as follows:

Definition 1 (Two-Stage Pricing-Usage Game)**.**

- Stage I (Pricing-game $\mathcal{G}_P \triangleq \{\mathcal{K}, \mathcal{P}, \{v_k\}_{k\in\mathcal{K}}\}$):
  Under the links' usage profile $\mathbf{x}$*, each provider* $k \in \mathcal{K}$ *chooses* p_k *to maximize its revenue* v_k*, given other providers' pricing strategies* $\mathbf{p}_{-k}$*. The pricing equilibrium is a joint pricing profile* $\mathbf{p}^* = (p_1^* \cdots, p_K^*)$ *such that*

$$p_k^* = \arg\max_{p_k\in\mathcal{P}_k} v_k(p_k, \mathbf{p}_{-k}^*, \mathbf{x}),\ \forall k \in \mathcal{K}. \tag{1-3}$$

- Stage II (Usage-game $\mathcal{G}_U \triangleq \{\mathcal{L}, \mathbb{R}_+^L, \{u_i\}_{i\in\mathcal{N}}\}$):
  Given providers' pricing profile $\mathbf{p}$*, each link* $(i,k) \in \mathcal{L}$ *chooses a usage demand* x_i^k *to maximize her payoff* u_i *given other links' usage profile* $\mathbf{x}_{-(i,k)}$*. The link demand equilibrium is a joint usage profile* $\mathbf{x}^* = (\mathbf{x}_1^*, \mathbf{x}_2^*, \cdots, \mathbf{x}_K^*)$ *such that no user can increase its payoff by unilaterally changing its usage profile:*

$$x_i^{k*} = \arg\max_{x_i^k\in\mathbb{R}_+} u_i(x_i^k, \mathbf{x}_{-(i,k)}^*, \mathbf{p}),\ \forall i \in \mathcal{N}. \tag{1-4}$$

The equilibrium solution of the game (if exists) would provide a satisfying solution in the sense that any unilaterally deviation from the equilibrium solution would lead to a payoff degradation. By convention, we appeal to the backward induction approach[9] to analyze the Stackelberg game. Next, we first study the usage game in Stage II.

1.4 Link Demand Equilibrium for Usage game

In this section, we study the usage demand over links given the joint pricing profile of service providers. Using function (1-1) and the first-order condition, $\frac{\partial u_i}{\partial x_i^k} = 0$, we obtain the best response function of link (i,k) as

$$\mathbf{B}_i^k\left(\mathbf{x}_{-(i,k)}\right) = \max\left\{0, \frac{a_i - p_k}{b_i + c} - \frac{b_i \sum_{k' \neq k} x_i^{k'}}{b_i + c}\right.$$
$$\left. + \frac{\sum_{j \neq i} g_{ij} \sum_{m \neq k} x_j^m}{b_i + c} + \frac{\sum_{j \neq i} (g_{ij} - c) x_j^k}{b_i + c}\right\}. \tag{1-5}$$

According to (1-5), the best response of each link consists of two parts: the internal demand, $\frac{a_i - p_k}{b_i + c}$, which is independent of other links, and the external demand, $-\frac{b_i \sum_{k' \neq k} x_i^{k'}}{b_i + c} + \frac{\sum_{j \neq i} g_{ij} \sum_{m \neq k} x_j^m}{b_i + c} + \frac{\sum_{j \neq i} (g_{ij} - c) x_j^k}{b_i + c}$, which depends on those links that are owned by the same user or are connected with the same service provider. Specifically, the first term $-\frac{b_i \sum_{k' \neq k} x_i^{k'}}{b_i + c}$ characterizes the negative effect on link (i,k) from other links starting from user i, implying that the data usage from providers other than k would dampen the usage from service provider k. The second term $\frac{\sum_{j \neq i} g_{ij} \sum_{m \in \mathcal{K}} x_j^m}{b_i + c}$ indicates the level of positive network effect on link (i,k) from the links that connect user i's social neighbors and service providers excluding k. The coefficient $\frac{g_{ij} - c}{b_i + c}$ characterizes the marginal impact on the demand of link (i,k) from other links that also connect with provider k. Clearly, if the social effect dominates the congestion effect (i.e., $g_{ij} \geq c$), the marginal impact is positive; while if the congestion effect dominates (i.e., $g_{ij} < c$), the marginal impact is negative.

1.4.1 Existence and Uniqueness of Link Demand Equilibrium

We first discuss the existence of a link demand equilibrium for the usage game. Without loss of generality, we focus only on the links with positive usage, as those links with zero usage are strategically redundant to the network. Let $\mathcal{L}^+$ denote the set of links with positive data usage, i.e., $x_i^k > 0, \forall (i,k) \in \mathcal{L}^+$, and define $\tau : \mathcal{L}^+ \to (1, 2, \cdots, L^+)$ as a mapping, such that $\tau(i,k)$ labels the link $(i,k) \in \mathcal{L}^+$ with an index $l \in \{1, \cdots, L^+\}$[4]. For convenience, let $\mathbf{u}^+ = (u_1^+, \cdots, u_{L^+}^+)$ denote the utility vector with $u_{\tau(i,k)}^+ = u_i$, $\mathbf{x}^+ = (x_1^+, \cdots, x_{L^+}^+)$ denote the usage vector with $x_{\tau(i,k)}^+ = x_i^k$, $\mathbf{p}^+ = (p_1^+, \cdots, p_{L^+}^+)$ denote the price vector with $p_{\tau(i,k)}^+ = p_k$ indicating the service price on link (i,k), and $\mathbf{a}^+ = (a_1^+, \cdots, a_{L^+}^+)$ denote the coefficient vector with $a_{\tau(i,k)}^+ = a_i$ representing the intrinsic coefficient of link (i,k). We illustrate the notation rules via an example as shown in Fig. 1-2, where the system consists of three service providers and four mobile users. Accordingly, we have $L^+ = |\mathcal{L}| = 9$, $\mathbf{a}^+ = (a_1, a_1, a_1, a_2, a_2, a_3, a_3, a_3, a_4)$, and $\mathbf{p}^+ = (p_1, p_1, p_1, p_2, p_2, p_3, p_3, p_3, p_4)$.

[4] In particular, we have $\tau(i,k) < \tau(i,k')$, if $k < k'$ and $\tau(i,k) < \tau(i',k)$, if $i < i'$, $\forall i, i' \in \mathcal{N}$, and $\forall k, k' \in \mathcal{K}$.

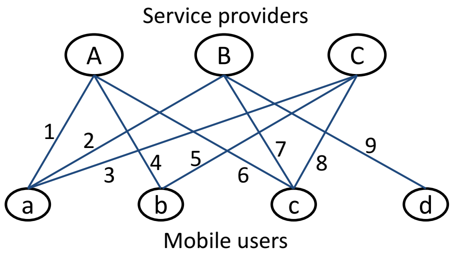

图 1-2 Illustration of a system with three service providers and four mobile users with nine positive usage links.

In the sequel, we show that all the link demand equilibria of the usage game $\mathcal{G}_U^+ \triangleq (\mathcal{L}^+, \mathbb{R}_+^L, \{u_i\}_{i\in\mathcal{N}})$ are the solutions to the following linear complementarity problem (LCP)[34] formed based on the best response function (1-5), as presented in Lemma 1.

Lemma 1. *Given price vector $\mathbf{p}^+$, a joint usage profile $\mathbf{x}^{+*} \in \mathbb{R}_+^{L^+}$ is a link demand equilibrium of game $\mathcal{G}_U^+$, if and only if $\mathbf{x}^{+*}$ is the solution to the linear complementarity problem $LCP(W, \mathbf{x}^+)$ defined by the following inequalities:*

$$\begin{cases} \mathbf{x}^+ > 0 \\ \mathbf{a}^+ - \mathbf{p}^+ - W\mathbf{x}^+ \leq 0 \\ (\mathbf{x}^+)^T(\mathbf{a}^+ - \mathbf{p}^+ - W\mathbf{x}^+) = 0 \end{cases}, \tag{1-6}$$

where W is a $L^+ \times L^+$ weighted adjacency matrix with the element at row $\tau(i,k)$ and column $\tau(i',k')$ defined as follows:

$$w_{\tau(i,k),\tau(i',k')} = \begin{cases} b_i + c, & \textit{if } i = i', k = k'; \\ b_i, & \textit{if } i = i', k \neq k'; \\ c - g_{ii'}, & \textit{if } i \neq i', k = k'; \\ -g_{ii'}, & \textit{if } i \neq i', k \neq k'. \end{cases} \tag{1-7}$$

Firstly, we claim the existence of a link demand equilibrium for the usage game.

定理 1.1. *The existence of a link demand equilibrium $\mathbf{x}^{+*}$ is guaranteed for the link usage game $\mathcal{G}_U^+$.*

The proof is straightforward given the fact that the set of link best responses defines a continuous mapping from a convex compact subset of a Euclidean space into itself, based on which we can use Brouwer's fix-point Theorem to demonstrate the existence of a link demand equilibrium.

Next, based on Lemma 1, we show the uniqueness of the link demand equilibrium under the following conditions.

定理 1.2. *Under the diagonal dominance condition of matrix W, that is, $\forall(i,k) \in \mathcal{L}$,*

$$\begin{cases} w_{(\tau(i,k),\tau(i,k))} \geq \sum_{(i',k') \in \mathcal{L}/(i,k)} |w_{\tau(i,k),\tau(i',k')}|, \\ w_{(\tau(i,k),\tau(i,k))} \geq \sum_{(i',k') \in \mathcal{L}/(i,k)} |w_{\tau(i',k'),\tau(i,k)}|, \end{cases} \tag{1-8}$$

the link usage game $\mathcal{G}_U^+$ admits a unique link demand equilibrium, given by

$$\mathbf{x}^{+*} = W^{-1}(\mathbf{a}^+ - \mathbf{p}^+). \tag{1-9}$$

The proof of Theorem 1.2 follows from the fact that under the condition (1-8), the linear complementarity problem $LCP(W, \mathbf{x}^+)$ defined in (1-6) corresponds to a concave game, thus has a unique solution $\mathbf{x}^{+*}$. Since the solution of problem $LCP(W, \mathbf{x}^+)$ corresponds to the equilibrium of the game $\mathcal{G}_U^+$ as indicated by Lemma 1, we can thereby establish the conditional uniqueness of the link demand equilibrium. The detailed proof has been relegated to the Appendix A. As shown in (1-9), we can explicitly express the link usage equilibrium as a linear combination of $\mathbf{a}^+$ and $\mathbf{p}^+$. As a result, the usage consumption of each user $i \in \mathcal{N}$ under the link demand equilibrium, $\sum_{k \in \mathcal{K}} x_{\tau(i,k)}^{+*}$, should be a linear function of $\mathbf{a} = (a_1, \cdots, a_N)$ and $\mathbf{p} = (p_1, \cdots, p_K)$.

1.5 Pricing Game among Rational Service Providers

In the previous section, we have shown the existence and uniqueness of the link demand equilibrium for the usage game in Stage II. Next, we move on to the determination of service prices for wireless providers in Stage I. Theoretically, each service provider can optimize his revenue over a continuous price variable. While in practice, the price announced by the service provider usually falls within a discrete sample space with a probabilistic distribution specified over a set of discrete price levels. To capture this feature, our discussion focuses on the pricing game that service providers maximize their expected revenues via choosing probabilistic pricing strategies against other users' strategies. In this section, we consider the conventional scenario where rational service providers evaluate their own revenue and other users' strategies objectively. We establish the existence of a mixed-strategy pricing equilibrium for the game.

1.5.1 Existence of Mixed-strategy Pricing Equlibrium

We define the mixed-strategy of provider k as $\pi_k = (\pi_k(p_k^1), \pi_k(p_k^2), \cdots, \pi_k(p_k^{M_k})) \in \Delta\mathcal{P}_k$, where $\pi_k(p_k^m) \in [0,1]$ is the probability that provider k chooses price $p_k^m \in \mathcal{P}_k$, with $\sum_{m=1}^{M_k} \pi_k(p_k^m) = 1$. A joint mixed-strategy pricing profile $\pi = (\pi_1, \cdots, \pi_K)$ is defined as a joint probability distribution over the Cartesian product $\Delta\mathcal{P} \triangleq \prod_{k\in\mathcal{K}} \Delta\mathcal{P}_k$. Following Von Neumann-Morgenstern's Expected Utility Theory (EUT)[7], the revenue of a provider $k \in \mathcal{K}$ under mixed strategies, denoted by z_k^{EUT}, can be written as

$$z_k^{EUT}(\pi_k, \pi_{-k}) = \sum_{\mathbf{p}\in\mathcal{P}} \left(\prod_{k\in\mathcal{K}} \pi_k(p_k) \right) v_k, \tag{1-10}$$

where $\pi_{-k} \in \prod_{k'\in\mathcal{K}, k'\neq k} \Delta\mathcal{P}_{k'}$ denotes the mixed strategies of all other providers except provider k. Here, v_k can be calculated according to (1-2), in which the aggregated consumption is obtained from the link demand equilibrium $\mathbf{x}^{+*}$ of Stage I (as discussed in Section 1.4).

We redefine the pricing game under Expected Utility Theory as $\mathcal{G}_P^{EUT} \triangleq (\mathcal{K}, \Delta\mathcal{P}, \{z_k^{EUT}\}_{k\in\mathcal{K}})$. The mixed-strategy Nash equilibrium for the pricing game is defined as follows.

Definition 2 (Mixed-strategy Pricing Equilibrium)**.** *The mixed-strategy pricing profile $\pi^* = (\pi_1^*, \cdots, \pi_K^*) \in \Delta\mathcal{P}$ is a mixed-strategy pricing equilibrium, if for every service provider $k \in \mathcal{K}$, we have*

$$z_k(\pi_k^*, \pi_{-k}^*) \geq z_k(\pi_k, \pi_{-k}^*), \ \forall \pi_k \neq \pi_k^*. \tag{1-11}$$

In the following Theorem, we show the existence of a mixed-strategy pricing equilibrium for the game $\mathcal{G}_P^{EUT}$.

定理 1.3. *There exists at least one mixed-strategy pricing equilibrium $\pi^* \in \Delta\mathcal{P}$ for the pricing game $\mathcal{G}_P^{EUT}$.*

证明. According to our model, each wireless service providers $k \in \mathcal{K}$ sets the price from M_k pricing strategies. Since both the number of service providers and the pricing strategy space of each service provider are finite, the pricing game $\mathcal{G}_P^{EUT}$ falls into the class of finite game. A mixed-strategy pricing equilibrium π^* is a fixed point of the best-response correspondence. By the Kakutani's fixed point theorem, the existence of at least one mixed-strategy Nash equilibrium is guaranteed for the pricing game $\mathcal{G}_P^{EUT}$ [9]. □

In practice, to avoid slow convergence time and unnecessary overhead of finding equilibria, we can consider approximate equilibrium solutions that fall within a small enough neighborhood of the mixed-strategy Nash Equilibrium. Consider an ϵ-pricing equilibrium defined as follows:

Definition 3 (ϵ-Pricing Equilibrium)**.** *A mixed-strategy pricing profile* $\pi^* = (\pi_1^*, \cdots, \pi_K^*) \in \Delta\mathcal{P}$ *is an* ϵ*-pricing equilibrium, if for each service provider* $k \in \mathcal{K}$*, we have*

$$z_k(\pi_k^*, \pi_{-k}^*) \geq z_k(\pi_k, \pi_{-k}^*) + \epsilon, \ \forall \pi_k \neq \pi_k^*. \tag{1-12}$$

The existence of an ϵ-Pricing Equilibrium follows directly from Theorem 1.3. To explicitly search for an ϵ-pricing equilibrium, we can resort to a centralized algorithm proposed in Section V of our previous paper[33].

1.6 Pricing Game among Service Providers with Bounded Rationality

In Section V, service provider's revenue is modeled based on Expected Utility Theory assuming fully rational providers acting objectively during the pricing competition. However, it has been observed that, sellers' behavior in practice usually deviate from the rational path predicted by this classic Expected Utility Theory[10]. Specifically, service providers may have subjective evaluation on the probabilistic pricing strategy of their opponents as well as their own revenue functions, which are used for decision making. In order to capture such behavioral factors in our proposed pricing game, we resort to Prospect Theory (PT).

1.6.1 Provider's Expected Revenue under Prospect Theory

We consider two main features of Prospect Theory. The first one is the *probability distortion effect*, which states that decision maker is prone to overweigh events with small probability, but underweight medium and large probability events. Specifically, this characteristic can be captured by a probability distortion function $w(p)$ that maps an objective probability p to a subjective one.

A widely used probability distortion function is the Prelec function[35]:

$$w(p) = \exp(-(-\ln p)^{\alpha}), 0 < \alpha \leq 1, \tag{1-13}$$

where p is the real probability of an event, α is the probability distortion parameter, and $w(p)$ is the corresponding subjective probability. Fig. 1-3 illustrates the probability distortion function (2-7) with different parameters. We can see that all the curves intersect at the point $1/e$. Besides, we have when $0 \leq p < 1/e$, the function is convex, and $w(p) < p$ (under-weighting); when $1/e \leq p < 1$, the function is concave, and we have $w(p) \geq p$ (over-weighting). A smaller value of distortion parameter α corresponds to a more significant probability distortion effect. When α is set to 1, the function reduces to the objective probability. In our work, we consider homogeneous service providers whose subjective evaluation can be characterized by the distortion function given in (2-7) with a same fixed value of α. Meanwhile, we assume that service providers are able to evaluate their own strategies objectively. Thus, user k's evaluation for a joint pricing strategy $\mathbf{p} \in \Delta\mathcal{P}$ under Prospect Theory can be expressed as $\pi_k(p_k)w(\prod_{k' \in \mathcal{K}, k' \neq k} \pi_{k'}(p_{k'}))$.

Another characteristic of Prospect Theory we considered is the *utility framing effect*. This effect captures the practical situation where each service provider has subjective evaluation of her own payoff. In practice, each user might consider her payoff as a gain only if it is above a reference point R (not necessarily equals zero), and consider it as a loss otherwise. Also, given the reference point R, the objective payoff is further tuned by a S-shaped monotone framing function $f(\cdot)$, which is concave at the side where $v > R$, and convex at the side where $v < R$. In addition, in the neighborhood of R, the losses loom larger than gains indicating that the marginal utility in losses is larger than in gains. In this work, we use a framing function based on the one proposed in[10],

$$f(x;R) = \begin{cases} (v-R)^{\beta}, & v \geq R \\ -\lambda(R-v)^{\beta}, & v < R \end{cases} \tag{1-14}$$

where the parameters $0 < \beta \leq 1$ and $\lambda \geq 1$ model the risk aversion and loss aversion respectively. Fig. 1-4 illustrates the framing function with different parameters. In particular, a larger β characterizes less degree of risk aversion when the player's payoff is away from the reference point; and a larger λ captures the greater loss experienced by the player with her payoff being reduced by a certain amount, in comparison to the corresponding gain she experiences with the same amount of the payoff increase. It is easy to see that when $\beta = \lambda = 1$, the subjective payoff boil down to the original objective payoff. We assume each service provider k evaluate her revenue using (1-14)

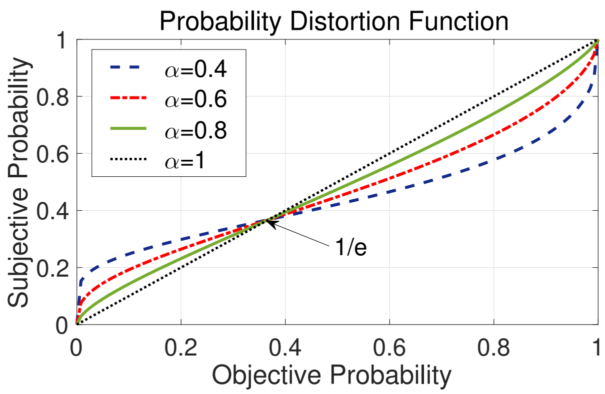

图 1-3 Probability distortion functions under different distortion parameters α.

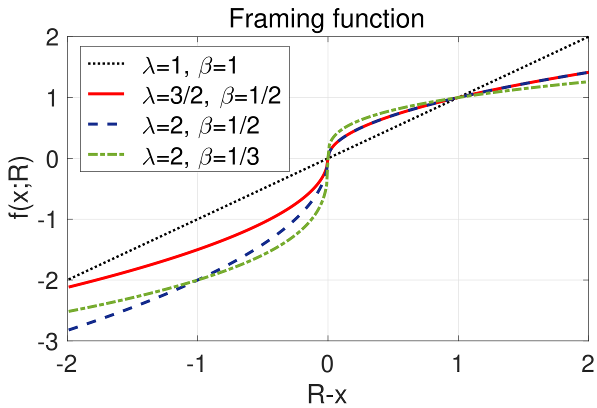

图 1-4 Framing functions under different utility aversion parameters β and loss penalty parameter λ.

with parameter β_k, and reference point $R_k, \forall k \in \mathcal{K}$. Under Prospect Theory model, the expected revenue z_k^{PT} of service provider $k \in \mathcal{K}$ can be written as

$$z_k^{PT}(\pi_k, \pi_{-k}) = \sum_{\mathbf{p} \in \mathcal{P}} \pi_k(p_k) w \left(\prod_{k' \in \mathcal{K}, k' \neq k} \pi_{k'}(p_{k'}) \right) f_k(v_k). \tag{1-15}$$

We denote the pricing game under Prospect Theory as $\mathcal{G}_P^{PT}\left(\mathcal{K}, \Delta\mathcal{P}, \{z_k^{PT}(R_k)\}_{k\in\mathcal{K}}\right)$, and revisit the existence of equilibrium solution for the pricing game in the next section.

1.6.2 Existence of Mixed-strategy Pricing Equlibrium

The mixed-strategy Nash equilibrium requires players optimally choosing their strategies given their beliefs of other players' strategies. The linearity of expected revenue (1-10) in probabilities plays a key role in establishing the existence of a mixed-strategy Nash equilibrium. However, as mentioned in the previous section, players will subjectively weight their beliefs modeled via non-linear distortion function on the probabilities under Prospect Theory. Thus, we need to reevaluate the existence of the pricing equilibrium of the game. We first provide the following definition for the mixed-strategy Nash equilibrium under Prospect Theory.

Definition 4 (Mixed-strategy Pricing Equilibrium under PT)**.** *We call a mixed-strategy profile $\pi^* = (\pi_1^*, \cdots, \pi_K^*) \in \Delta\mathcal{P}$ a mixed-strategy pricing equilibrium under Prospect Theory, if for each service provider $k \in \mathcal{K}$,*

$$z_k^{PT}(\pi_k^*, \pi_{-k}^*) \geq z_k^{PT}(\pi_k, \pi_{-k}^*), \ \forall \pi_k \neq \pi_k^*. \tag{1-16}$$

We show in the following Theorem that our pricing game $\mathcal{G}_P^{PT}$ admits a mixed Nash equilibrium under the condition that each service provider's reference point is fixed.

定理 1.4. *At least one mixed-strategy pricing equilibrium $\pi^* \in \Delta\mathcal{P}$ is guaranteed for the pricing game $\mathcal{G}_P^{PT}$, if service providers' reference points $\{R_k\}_{k\in\mathcal{K}}$ are all fixed.*

证明. For each $k \in \mathcal{K}$, given any $R_k \in \mathbb{R}$ and $\pi_{-k} \in \Delta\mathcal{P}_{-k}$, the expected revenue $z_k^{PT}(\pi_k, \pi_{-k})$ is linear in $\pi_k(p_k)$ for each $p_k \in \mathcal{P}_k$. As $\Delta\mathcal{P}_k$ is compact, the set of best responses strategies: $\mathbf{B}_k(\pi_{-k}) \triangleq \{\pi_k' \in \Delta\mathcal{P} : z_k^{PT}(\pi_k', \pi_{-k}) \geq z_k^{PT}(\pi_k, \pi_{-k})\}$ is nonempty, compact and convex valued. Note that π_{-k} enters $z_k^{PT}(\cdot)$ via $w(\cdot)$ in the form of $\pi_{-k}(p_{-k}) = \prod_{k'\in\mathcal{K},k'\neq k} \pi_{k'}(p_{k'})$. Since the probability distortion function $w(p)$ given in (2-7) is continuous in p, $z_k^{PT}(\pi_k, \pi_{-k})$ is continuous in π_{-k} for each $\pi_{-k} \in \Delta\mathcal{P}_{-k}$. By Berge's Maximum Theorem, the correspondence $B_k(\pi_{-k})$ is upper hemicontinuous. And by Kakutani's Fixed Point Theorem, there exists some $\pi^* \in \Delta\mathcal{P}$ such that $\pi_k \in B_k(\pi_{-k})$ for all $k \in \mathcal{K}$. Therefore, the claim in the Theorem 1.4 holds. □

Remarks. Our discussion about the existence of mixed-strategy pricing equilirbium under Prospect Theory is for fairly common case where service providers' reference points $\{R_k\}_{k\in\mathcal{K}}$ are fixed and determined solely by service providers themselves. Nevertheless, when the reference points are not fixed, it can be easily shown that the mixed-strategy pricing equilibrium might not exist even for a two-player case, where each player has two pure pricing strategy. If the reference point of service provider k is also dependent on others, the equilibrium analysis will become even complicated.

1.6.3 Distributed Learning Algorithm for Finding Mixed-strategy Pricing Equilibrium

In this section, we develop the algorithm for service providers of bounded rationality to find a mixed-strategy pricing equilibrium. One main challenge is raised by the utility framing effect of Prospect Theory model. Specifically, the parameters β_k and R_k are all private information only known to service provider $k \in \mathcal{K}$. As a result, no centralized party has the knowledge of all service providers' utility function, which are necessary for calculating an ϵ-mixed-strategy Nash equilibrium.

To tackle this challenge, we resort to distributed Fictitious Play based learning algorithm, through which players can learn to play out the equilibrium strategies via observations of their opponents' actions. Given the direct connection between the Nash equilibrium and the best response, it is expected that a Nash equilibrium should be obtained if the beliefs converge successfully at the end of the algorithm. However, such kind of standard Fictitious Play algorithm does not always work well: the beliefs can not converge for some games; in some other cases, although the beliefs converge, the mixed-strategy or the payoff does not converge. The non-convergence of strategies and payoffs in standard Fictitious Play is due to the fact that played strategy is not a continuous function of beliefs. Therefore, we employ the Stochastic Fictitious Play algorithm, a modified version of Fictitious Play, in which each player makes smooth best response instead of the standard best response.

Definition 5 (Smooth Best Response)**.** *For each player $k \in \mathcal{K}$ with payoff $z_k^{PT}(\pi_k, \pi_{-k})$, given its opponents' joint mixed-strategy π_{-k}, the smooth best response $\mathbf{b}_k(\pi_{-k};\eta) \in \Delta\mathcal{P}_k$ corresponds to the mixed-strategy defined as:*

$$\mathbf{b}_k(\pi_{-k};\eta) = \underset{\pi_k \in \Delta\mathcal{P}_k}{\arg\max} \left\{ z_k^{PT}(\pi_k, \pi_{-k}) + \frac{1}{\eta} E(\pi_k) \right\}, \tag{1-17}$$

where $\eta > 0$ is a temperature parameter and $E(\pi_k) : \Delta\mathcal{P}_k \to \mathbb{R}$ is a strictly differentiable and concave function, causing an infinite slope of $E(\pi_k)$ as π_k approaches the boundary of $\Delta\mathcal{P}_k$.

Since the smooth best response is continuous in π_{-k}, convergence of beliefs implies convergence of mixed strategies. We employ the commonly used entropy-form smooth-function $E(\pi_k) = -\sum_{m=1}^{M_k} \pi_k(p_k^m) \ln \pi_k(p_k^m)$. As a result, when $\eta \to \infty$, the smooth best response $\mathbf{b}_k(\pi_{-k};\eta)$ reduce exactly to the best response. On the other extreme, as $\eta \to 0$, the entropy part is maximized so that a uniform distribution is assigned to the set of available price levels. It can be shown that, the smooth best response for each price level $p_k^m \in \mathcal{P}_k$ is in the form of Gibbs-Boltzmann rule:

$$\mathbf{b}_k(\pi_{-k};\eta)(p_k^m) = \frac{\exp[\eta z_k^{PT}(p_k^m, \pi_{-k})]}{\sum_{p_k^n \in \mathcal{P}_k} \exp[\eta z_k^{PT}(p_k^n, \pi_{-k})]}. \tag{1-18}$$

Next we describe the learning algorithm (as outlined in Algorithm 1) in details. At the initialization stage, each service provider $k \in \mathcal{K}$ sets her initial mixed pricing strategy $\pi_k^{(0)}$ over her pricing strategy space $\mathcal{P}_k$, based on which she chooses an initial pricing level. After the initialization, each provider can have the revision opportunity only after waiting for a random back-off time sampled from an exponential distribution with rate τ, i.e., an asynchronous strategy updating process[5]. At stage t, each service provider $k \in \mathcal{K}$ observes her opponent l's current action and updates her belief as follows[36]:

$$\begin{aligned} \pi_l^{(t)}(p_l^m) = \pi_l^{(t-1)}(p_l^m) + \frac{1}{t}\left\{\mathbb{1}_{\{p_l^{(t)}=p_l^m\}} - \pi_l^{(t-1)}(p_l^m)\right\}, \\ \forall p_l^m \in \mathcal{P}_l. \end{aligned} \tag{1-19}$$

When service provider k updates the price level, she first calculates her expected payoff under all possible actions with respect to the current beliefs of her opponents (i.e., $z_k^{PT(t)}(p_k^m, \pi_{-k}^{(t)}), \forall p_k^m \in \mathcal{P}_k$). Then she makes the smooth best response by randomly selecting a price level with respect to the distribution $\mathbf{b}_k(\pi_{-k}^{(t)};\eta) = \left(\mathbf{b}_k(\pi_{-k}^{(t)};\eta)(p_k^1), \cdots, \mathbf{b}_k(\pi_{-k}^{(t)};\eta)(p_k^{M_k})\right)$ as calculated according to (1-18). Finally, she evolves the learning of her mixed-strategy by

$$\pi_k^{(t)} = (1-\theta^t)\pi_k^{(t-1)} + \theta^t \mathbf{b}_k(\pi_{-k}^{(t)};\eta). \tag{1-20}$$

where $\theta^t > 0$ denotes the learning rate.

We next analyze the convergence of Algorithm 1. As mentioned above, the use of Stochastic Fictitious Play inherently guarantees that the convergence of beliefs leading to the convergence of mixed strategies. Thus, proving the convergence of the algorithm to a mixed-strategy Nash equilibrium is equivalent to proving the convergence of service providers' beliefs. In comparison to the standard Fictitious Play, using stochastic Fictitious Play induces a gap between the original mixed-strategy pricing equilibrium and the achievable ϵ-mixed-strategy pricing equilibrium, as the tradeoff of better convergence performance. Our main results for the convergence of Algorithm 1 are given as follows:

[5]Appealing to the property of exponential distribution, the probability that more than one providers simultaneously update their channel selection strategies equals to zero.

Algorithm 1: Distributed Learning Algorithm

initialization:
  for all $k \in \mathcal{K}$ **do**
    Initialize a uniform distribution $\pi_k^{(0)}$ over space $\mathcal{P}_k$.
    Initialize

$$\mathbf{z}_k^{PT(0)} = \left(z_k^{PT(0)}(p_k^1, \pi_{-k}^{(0)}), \cdots, z_k^{PT(0)}(p_k^{M_k}, \pi_{-k}^{(0)}) \right).$$

end initialization
loop for each service provider $k \in \mathcal{K}$ in parallel:
  Set up a timer with the value sampled from an exponential distribution with mean equal to $\frac{1}{\tau}$.
  Count down until the timer expires.
  $t \leftarrow t + 1$
  Update the beliefs of other service providers according to (1-19).
  if service provider k's timer expires **then**
    Calculate the smooth best response $\mathbf{b}_k(\pi_{-k}^{(t)}; \eta)$ according to (1-18) and update the price level using smooth best response.
    Update the mixed-strategy $\pi_k^{(t)}$ according to (1-20).
  end if
end loop

定理 1.5 (Convergence of Algorithm 1)**.** *With the temperature parameter $\eta > 0$, Algorithm 1 converges almost surely to an ϵ-mixed-strategy pricing equilibrium, i.e., $\forall k \in \mathcal{K}$,*

$$\lim_{t \to \infty} \pi_k^{(t)} = \pi_k^* \tag{1-21}$$

with

$$\epsilon(\eta) = \max_{k \in \mathcal{K}} \left(\frac{1}{\eta} \ln(|\mathcal{P}_k|) \right). \tag{1-22}$$

Due to the space limitation, the proof is omitted here and is provided in the Appendix B.

Remarks. The use of smooth best response results in an exploration-exploitation trade-off, which is consistent with our assumption that service providers, as players of the game, are of bounded rationality. On one hand, the action with larger expected revenue will be chosen with a higher probability, which can be regarded as the exploitation aspect of a better strategy (rational behavior). On the other hand, all of the actions with positive probability might be selected, which enables the exploration of the strategy space (bounded rational behavior). And the 'temperature' parameter η is employed to control this trade-off.

1.7 仿真验证

We evaluate the system performance of the oligopoly wireless service market via numerical results in this section. For ease of exposition, we consider a duopoly market including N socially connected mobile users and two wireless providers A and B.

We have used the Erdős-Rényi (ER) graph model[37] for the underlying social network among mobile users[5]. Specifically, the undirected social tie between each pair of users exists with a fixed probability e, whose value characterizes the dense level of the particular social network. We further let the weight of an existed social tie g_{ij} between user i and j following a normal distribution $\mathcal{N}(\mu_G, 1)$. For each user i, the intrinsic coefficients a_i and b_i follow the normal distributions $\mathcal{N}(\mu_a, 5)$ and $\mathcal{N}(\mu_b, 5)$, respectively. The parameters have the following default values: $N = 10$, $e = 0.5$, $\mu_a = \mu_b = 20$, $c = 1$, $q_A = 1$ and $q_B = 3$. The price space for each service provider is set to be $\mathcal{P}_A = \mathcal{P}_B = \{0.96, 0.98, 1.00, 1.02, 1.04, 1.06, 1.08, 1.10\}$.

We first consider the scenario with rational service providers and simulate the pricing-usage game using the algorithm proposed in our previous paper[33], with parameter ϵ set to be 0.4. To evaluate the impact of enhancing network effect on users' data usage at equilibrium, we increase

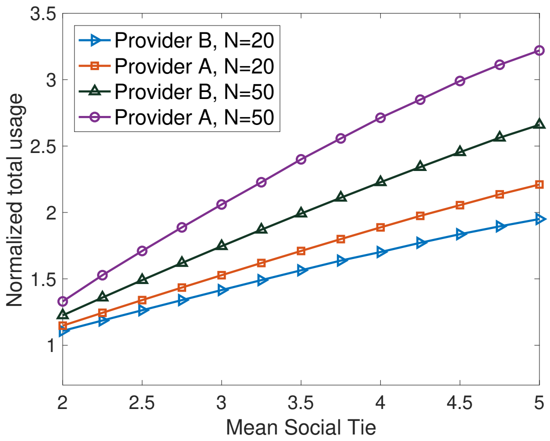

图 1-5 Impact of mean of social tie μ_G on total data usage.

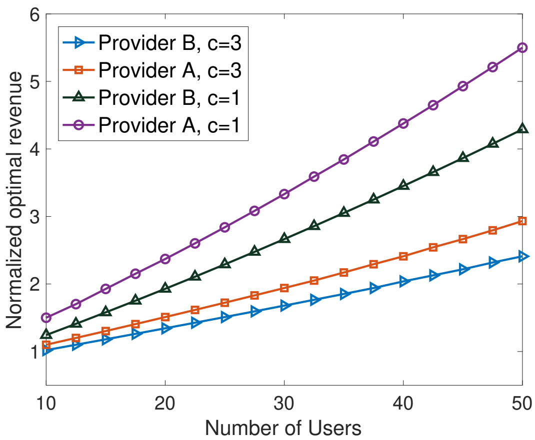

图 1-6 Normalized optimal revenue versus number of users N.

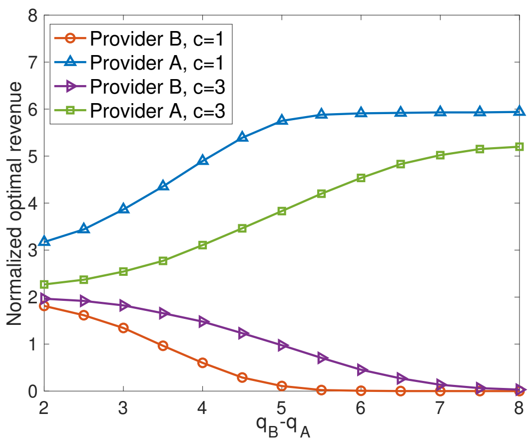

图 1-7 Normalized optimal revenue versus service cost difference.

the mean social tie strength μ_G from 2 to 5, for a market with 20 users and one with 50 users respectively, letting the congestion coefficient being set as default. Fig. 1-5 illustrates that mobile users' normalized total usage increases monotonically with μ_G, and the normalized total usage is

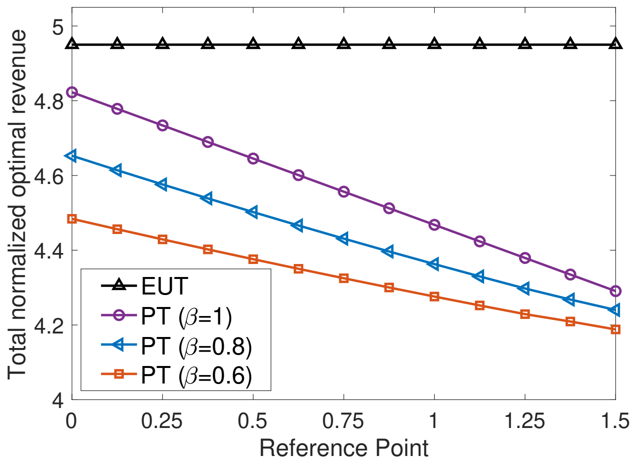

图 1-8 Impact of bounded rationality on service providers' total revenue.

greater for the case with 50 users. This result clearly demonstrates that strengthened social connections, hence a stronger network effect, can push the mobile users to consume more data from service providers.

We then turn to evaluate the attainable revenues for the wireless service providers. We fix the mean social tie strength as $\mu_G = 2$ and simulate the system with user amount changing from 10 to 50, for both a light congestion scheme ($c = 1$) and a heavy congestion scheme ($c = 3$). As illustrated in Fig. 1-6, the service providers' normalized revenues at equilibrium increase monotonically as the size of market increases. Also, as expected, service providers receive higher revenues when the congestion level is lower.

We next evaluate the impact on the normalized revenues from the competition between the two service providers. We set $q_a = 1$ and changed q_b from 3 to 9 so that the service cost difference was altered from 2 to 8 (provider A is more competitive compared to provider B in terms of the service cost). As illustrated in Fig. 1-7, with the enlarging cost difference, service provider A has an increasing normalized revenue while the revenue of provider B keeps decreasing. At a certain level of cost difference, the revenue of provider B diminishes to zero and the revenue of provider A becomes saturated, which means that all users choose to consume data from service provider A.

At last, we investigate the impact of rationality of service providers by comparing the optimal revenue under the PT model (via using Algorithm 1) to the one under the conventional EUT model. For the case with PT model, we choose the same reference point and utility aversion parameter for both service providers (i.e., $R_A = R_B = R$, $\beta_A = \beta_B = \beta$). We further set the probability distortion parameter $\alpha = 0.6$ and the loss penalty parameter $\lambda = 1.5$. For the distributed learning algorithm, we set the learning parameter $\theta^t = 1/t$, and the temperature parameter $\eta = 5$. We choose three different values for the utility aversion parameters (i.e., $\beta = 1, 0.8, 0.6$), and run the simulation with R increasing from 0 to 3. As illustrated in Fig. 1-8, the total revenue decreases as the reference point increases. In essence, a larger reference point will lead to a greater shift of service providers' objective evaluation, so that they value less on their gain but more on their loss. In addition, a smaller value of β leads to further degradation of revenue since service providers value their gain less when they become more gain-averse. It is also shown that the degradation due to smaller β reduces as the reference point increases. We eliminate the impact of parameter β by setting $\beta = 1$; the gap between the EUT curve and PT curve at $R = 0$ indicates the revenue degradation solely due to the probability distortion effect.

1.8 本章小结

In this paper, we explored the wireless service providers' pricing strategies and mobile users' data consumption behavior. To characterize the interactions between mobile users and service providers, we appealed to the Stackelberg game model and analyzed its equilibrium solution. Particularly, we first solved the link demand equilibrium in Stage II of the game and showed its uniqueness property. We then established the existence of a mixed-strategy pricing equilibrium in Stage I, under both the conventional scenario with rational service providers and the more realistic scenario with bounded rational providers. Our numerical results provide insight on the impact of positive network effect and congestion effect over the system performance, as well as the negative influence on service providers' revenues caused by their bounded rational behavior.

For future work, we will consider alternative model to better characterize the congestion effect. Another future direction is to conduct some real-data based experiment to verify the impacts of network effect and congestion effect on the system performance.

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