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無線行動網路之區域媒體接取協定設計

Medium Access Control (MAC) Design in Wireless Mobile Local Area Network (LAN)

趙式隆

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口試委員會審定書

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本論文係趙式隆君 (D97921031) 在國立臺灣大學電機工程學研究所完成之碩士學位論文，於民國 106 年 7 月 22 日承下列考試委員審查通過及口試及格，特此證明

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誌謝

自 2004 年進入台大電機系開始，我當了 13 年的學生。其中，從 2006 年大學部修專題研究開始學習無線行動網路，2008 年直攻博士班，到 2017 年本論文的完稿，就經歷了 11 年。在這段時間裡，通訊協定標準技術也發生了跨世代的演化，從第二代行動通訊技術 2G，到了第五代 5G 的時代。本論文選擇了我做得最差跟最好的兩個研究作為代表，也是我的第一個跟最後一個研究，可以說是歷史文件了。這麼多年來，我完成了很多的事情，從無到有創造了很多東西，唯一沒有改變的是博士論文始終沒有寫成，更遑論學位。我一直都是非常糟糕的學生，無論是在學術或對於實驗室的貢獻上都是不合格的，能夠終於在修業加上休學年限用盡的最後一個學期，留下一個碩士學位作為青春的紀念，也作為職業學生的一個句點，勉強也算是完成了社會期待的基本底線。在此想要特別感謝我的論文導師魏宏宇教授對於我任性的包容，除了一直以來的循循善誘之外，還給了我這樣不成材的學生一個口試的機會，對於老師的敬意只能說是無以復加。其次，想要特別感謝的是我的母親沈惠華女士與阿姨沈愛玲女士，抱歉讓您們失望了，沒能透過學術能力拿到的博士學位，只好未來捐系館拿榮譽博士了，這可能是比較務實的努力目標。我還想要感謝在這趟旅程最後幾年才加入的程子玲女士，認識妳是我在台大這幾年最好，最無可

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取代的事情。最後，在這場長達 13 年的功敗垂成的冒險裡面，很多的朋友或多或少，直接或間接讓我成長了不少。不過大家應該也沒有興趣翻開這本連我自己都覺得沒什麼閱讀價值的論文，因此我就不一一致謝了，反正大家也看不到。

生命是以時間為單位的，浪費別人的時間，等於謀財害命；浪費自己的時間，則等於慢性自殺。我沒有打算謀害大家，也請大家把時間浪費在更美好的事物上吧！

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摘要

創造無所不在的網際網路存取向來是電信業最重要的目標之一。為了達成這個目標，資源管理就自然成為在無線網路的驚人成長速度之下最重要的議題之一。近年來，隨著物聯網和智慧型裝置的成長，區域無線行動網路的去中心化更顯得重要。因此，在本論文中，我們提出了兩個分散式的媒體接取協定，用以解決在上述前提下分享和同步化的問題。

在本研究的第一部分，我們針對各類無線接取基站，提出了一個基於賽局理論的頻寬分享模型。我們將這個賽局裡的玩家分成三類，自私接取基站、無私接取基站和訂閱基站。我們考慮了兩種不同的接取基站，目的在換取收費的自私接取基站和提供免費服務的無私接取基站。在這個設定之下，我們透過決定分享的比例和訂閱基站決定是否加入服務，來得到賽局理論中所謂的均衡。在這個章節裡面，我們透過分析推導得到了納什均衡，並在結果部分提出了對應的通訊協定設計與數值效率評估。

在第二部分，我們提出了一個應用於裝置對裝置應用感知鄰近服務的分散式通訊機制。這個師法螢火蟲的仿生演算法，能夠同時達成鄰近探勘與同步化。更精確地說，這個機制不只同時達成鄰近裝置和服務發掘，也在達成在物理層通訊時間和和服務偏好的同步。然而，基

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礎的螢火蟲演算法無法完美地應用於大規模的分散式網路系統，例如像是基於進階長期演進技術 (LTE-A) 的裝置對裝置通訊。在大部分的網路拓樸，基於各種原因，節點裝置之間很可能無法聽到所有周邊的裝置將使得無拓樸概念的基礎螢火蟲演算法無法達成目標。因此，我們更近一步提出了螢火蟲生成樹演算法，用以解決因為節點拓樸所導致的無法收斂的問題。

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Abstract

Constructing ubiquitous internet access is always one of the most important targets for telecommunication industry. To achieve this goal, resource management has become a crucial issue in response to the remarkable growth of wireless networking. Currently, the ability for making wireless mobile LAN (local area networks) decentralized has become more crucial due to the growth of IOT (internet of things)and smart devices. In this thesis, two distributed MAC (medium access control) protocols are proposed for solving both the sharing and the synchronizing problems.

In the first part of this work, a game-theoretic bandwidth sharing formulation for wireless access points is proposed. We introduce three types of players: selfish access points, altruistic access points and subscriber stations. Two categories of access points are considered: selfish ones who charge, and altruistic ones who provide the free service. Under these settings, the derived game-theoretic equilibrium strategies can clearly determine rate allocation and describe ways subscriber stations joining the service. In this chapter, Nash Equilibrium is derived analytically and the results complement the distributed protocol designs and numerical performance evaluation.

In the second part, a distributed mechanism for application-aware proxim-

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ity services (ProSe) in device to device (D2D) communications is presented. The method, which is derived from the bio-inspired firefly algorithm, can achieve proximity discovery and synchronization at one time. To be precise, this mechanism not only enables neighbour discovery and service discovery simultaneously, but achieves synchronization in physical communication timing and service interests in the meanwhile. However, the basic firefly algorithm is not perfectly suitable for larger scale systems such as LTE-A D2D. In most network topologies, the property that each node may not be able to hear all its neighbours makes the basic version fail. Thus, we further propose the firefly spanning tree (FST) algorithm which can solve the topology-dependent divergence problems.

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Chapter 1

A Game Theoretic Model for Access Point Bandwidth Sharing

1.1 Introduction

IEEE 802.11 WLAN has enormous potential to make future network more accessible, and WiFi wireless network coverage is deemed as an significant factor in the future wireless internet. Such phenomenon can be observed from the rapid expansion of FON[1], the world's largest WiFi community. Broadband internet subscribers in such community can take advantage of the service networks by plugging customized wireless routers that connect to broadband internet connection, in addition to that, such routers can also work as WiFi access points. As the use of such cooperative service in wireless network is expanding around the world, sharing one's bandwidth is becoming an interesting and useful model. Since such access points mushroom worldwidely (e.g. FON access point has 80 percent coverage rate in Tokyo city), the subject of bandwidth management of these kinds of network services need to be further studied. In such services, user cooperation (i.e.,

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sharing spare bandwidth) makes all the difference to access coverage, but we are still uncertain about whether the users will not do this in an optimal way, i.e., balancing the profit from user subscriptions and their own bandwidth needs.

This chapter provides a game theoretic framework to model the emerging service sharing and using behavior. The Nash Equilibrium strategies for selfish and altruistic access points and subscriber stations are derived. In addition, we discuss the detailed practical protocol design. Distributed algorithms converging to equilibrium strategies are also formulated for practical implementation so that the it can be applied to present and future access point technologies. This chapter makes two major contributions: (1) it exposes the way users allocating rates for bandwidth sharing in access points and (2) the processes subscriber stations joining the service in a distributed fashion while optimizing individual objectives reflected in utility functions. Besides, the game-theoretic concept of "share and use" is also applicable in the emerging cognitive radio networks since they share the basic concepts. That is, the relationship between access points and subscriber stations in 802.11 is analogous to the bonding between primary and secondary users in 802.22. Thus the general techniques proposed in this chapter shows great potential to be applied to the field of cognitive radio.

We hereby introduce three types of players: subscriber stations, altruistic access points and selfish access points. An subscriber station (called Alien in FON) is anyone who use the WiFi access with a fee but does not share his connection. By contrast, as broadband network subscribers, the other two types of community members share part of their network bandwidth service either for free or for a profit. The former, altruistic access points, also known as Linus, are anyone who share his or her network service and enjoys free wireless access when roaming to other's wireless access points. And the latter, selfish

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access points, also known as Bill in FON community, are those in business who share their WiFi access and receive part of the revenue collected from Aliens for using the access points. In real world FON systems, just like Linuses (altruistic access points), Bills (selfish access points) also have gratuitous WiFi access roaming.

Game theory has been widely applied to resolve allocation problems in computing [2][3][5] and various networking problems [6][7][8] as it offers a suite of analytical techniques to model the interactions between players in various situations. Recognizing its structural characteristics, we apply game theory to model the bandwidth sharing strategies and the convergence of operation equilibria in the network. We focus on particular sets of strategy that each represents a best response to the others, which is also known as Nash Equilibria[9]. When the current set of strategy choices users have made reach a Nash Equilibrium, they would have no incentive to unilaterally deviate from their current choices, since changing their current strategy alone does not benefit them as the rest of others remain theirs unchanged.

The rest of the chapter is organized as follows: After the brief review of the previous works in Section 2, we give an overview of the modeling settings in Section 3. Then, we investigate the game theoretic model when Bill is the access point in Section 4, and when Linus is the access point in Section 5. After that, we illustrate a practical bandwidth sharing strategy that could be implemented in Section 6. In Section 7, we present the simulation results of user dynamic and Nash Equilibrium in various settings. After that, we show the versatility of our implementation in Section 8, then conclude the chapter in Section 9.

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1.2 Related Work

Our model is presented differently from the previous works in several aspects. First, Rakshit and Guha solve a distributed fair bandwidth sharing problem by applying a constrained Nash Equilibrium to resolve fairness issues among distributed selfish users[2]. Compared to our game model, this game theoretic model focuses on p-CSMA MAC layer random access control while ours focuses on pricing and adjustable bandwidth sharing.

Second, Lam, Chiu and Lui apply a game theoretic approach to study pricing as an incentive mechanism in wireless mesh network [4]. According to economical behavior, the interaction between access points, relaying nodes and clients from one-hop to multi-hop networks are analyzed under both the unlimited and limited capacity scenarios. Therefore, the fixed-rate non-interrupted service scheme we proposed is considered more likely to be practical as the core idea of their paper is to adjust price, while ours applies fixed-pricing policy and emphasizes on the optimization resource allocation without adjusting price.

Third, Musacchio and Walrand investigate the WiFi pricing problem with the Perfect Bayesian Equilibrium (PBE) concept [12]. The game theoretic models are formulated for two types of user utility functions: (1) Web browsing utility which increases linearly with time. (2) File transfer utility function which is a step function. Their work focuses on adjusting price for these two types of utility functions to achieve PBE. In contrast, our system adjusts bandwidth usage ratio and charge clients with a fixed price.

Fourth, Mittal, Belding and Suri use the concept of Nash Equilibrium to model the problem to select wireless access points[11]. This game theoretic work helps to capture selfish mobile user behaviors in WiFi access network, but the focus of access point selection is different from our bandwidth sharing problem.

Fifth, Yaiche, Mazumdar and Rosenberg solve the optimal and fair bandwidth alloca-

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tion problem for elastic traffic in high speed network by using Nash Bargaining Solution (NBS) concept [10]. The network resource allocation is resolved with dynamic pricing mechanism, and fixed amount of bandwidth is allocated to users based on users' bandwidth requirements and their budgets. Although we both apply the concept of logarithm utility to game formulation, we are different in user strategy spaces. We investigate a novel bandwidth sharing problem with fixed pricing and dynamic access point bandwidth sharing, which in many ways differs from theirs. Other than that, the Nash Equilibrium approach we adopt is also different from their NBS approach.

Sixth, Manshaei *et al.* use a game-theoretic approach to study the competition between a licensed band operator (LBO) and a wireless social community operator (SCO) for the subscription of users in a given area[13]. In this work, users select network service based on coverage and subscription fee, while our model, by contrast, emphasizes on the bandwidth sharing strategies in social community operators. In addition, our model can also be applied to model both selfish and altruistic cases.

Seventh, Mazloumian *et al.*[15] discuss wireless social community systems with adjustable subscription fees. They compute optimal prices with both static and semi-dynamic pricing which is achieved in incomplete information systems. Their basic model is also inspired by FON. In contrast, we model the system in another approach which is an adaptive bandwidth controlling scheme for a fixed price system. Also, the proposed algorithms based on our model is more applicable in real world systems.

Eighth, Sagduyu, Berry and Ephremides[16] discuss the problem of rate allocation. Similar to our model, they also have different player modeling from the traditional approaches. Specifically, they model the players as selfish and malicious transmitters. Contrast to their approach, we focus on identifying players as either selfish or altruistic ones.

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Also, their discussion focuses on the analytical process whereas ours on implementation for the real world system.

Nineth, Niyato and Hossain[17] discuss the spectrum sharing problem between a primary user and other secondary users in cognitive radio. They also investigate the sharing scheme in both stationary and dynamic conditions. However, the distinction between theirs and ours is that we design an applicable model for dynamic system whereas they model such system as a dynamic game.

Tenth, Chao, Lin and Wei[14] formulates the bandwidth sharing problem as a game. Specifically, the authors model mixed selfish and altruistic user behaviors in multihop relay networks. However, their paper is to compare the effects of different types of users coexisting in static wireless networks, our work, however, discusses the situations both in static and dynamic context.

Finally, the book[18] written by MacKenzie, Dasilva and Tranter, discusses several different game-theoretic applications in wireless networks. They also emphasize the importance of cooperation in wireless systems. Nevertheless, the importance and implementation method in this book seem to be ambiguous as the concept of bandwidth sharing is unclear. Therefore, our work is considered more comprehensive as it encompasses both the analytical methods and its implementation.

1.3 modeling as normal form games

1.3.1 Overview

We first formulate our system as normal form games to identify the best responses of users to prove the existence of a Nash Equilibria. As we mentioned earlier, there are three kinds

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Table 1.1: Characters in The Game Formulation

Player	Notation	Description	Strategy Space
Selfish AP: Bill	B_i	Bandwidth Sellers	$0 \leq x_{B_i} \leq 1$
Altruistic AP: Linus	L_i	Generous Bandwidth Givers	$0 \leq x_{L_i} \leq 1$
SS: Alien	A_i	Bandwidth Buyers	J, NJ
Free SS: Linus or Bill	LB_i	Free Roamers	Always Join the Service

of players: Bills, Linuses, and Aliens. Bills and Linuses are access points (APs) in the cooperative wireless networks, and Aliens are subscriber stations (SS) in the game. As the FON access points, the owner (i.e. Bill and Linus) of access points can configure the ratio of bandwidth to share.

In FON, people who share their WiFi connections at home are granted privilege to use all the network's wireless access points for free. In addition, we increase two more characters: Bill as an SS, and Linus as an SS. However, we do not consider them as players in our model since their uses are gratuitous as the only best strategy they have to choose is to join the game and enjoy the free bandwidth. Although their behaviors in a SS mode seem insignificant, their number still has a direct impact on our system as they share bandwidth equally with Aliens. Bandwidth sharing affects the decision-making of the players in the game, so the number of WLAN SSs is viewed as an environment parameter in this chapter.

Bills and Linuses can decide the proportions of the bandwidth that they would like to share or keep. But Alienes only have two choices, either join (J) or not join (NJ). With that in mind, we formulate two types of games, Bill-versus-Aliens and Linus-versus-Aliens. In a Bill versus Alien game, Bills decide the quantity of bandwidth to share (for profits) and Aliens decide whether to join the service or not. In a Linus versus Alien game, on the other hand, Linuses decide the quantity of bandwidth to share (for free) and Aliens decide whether to join the service or not.

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1.3.2 Utility Function

The concept of utility is commonly used in economics to refer the levels of satisfaction when the decision-makers receive the outcomes of their actions. Similarly, user preference could be represented as utility functions. We thereby define satisfaction term, S, to denote the satisfaction of using certain amount of bandwidth. Obviously, users can not execute any meaningful application while the bandwidth usage is less than a threshold ϵ. When the allocated bandwidth is less than ϵ,S is 0. Therefore, We adopt the widely used logarithmic utility to denote the satisfaction of using bandwidth [10]. When users' allocated bandwidth exceeds threshold ϵ, their levels of satisfaction increases logarithmically.

Definition 1 *Let b denotes the bandwidth that a user can use within the range of $b > 0$, $h > 0$ and $\epsilon \geq 1$. Then we have the satisfaction function:*

$$S(b) = \begin{cases} 0 & \text{if } b \leq \epsilon \\ h \ln(b) & \text{if } b > \epsilon. \end{cases}$$

In the following sections, several terms are presented in each utility function, including the satisfaction term derived from the above satisfaction functions.

In the normal form game, all the players of our games determine their strategies and gain their utility function values immediately. Players are assured to access enough information to decide their best responses. Note that the information for each player only includes the comprehensive system information before the games start. Like in the real world, each player does not know the exact utility functions of other players. Now, we discuss the utility functions of the three kinds of players.

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Table 1.2: Notations in the Game Theoretic Model

Notations	Descriptions
b	The bandwidth a user can use. $b > 0$.
h	The satisfaction coefficient. $h > 0$.
ϵ	Least bandwidth threshold. $\epsilon \geq 1$.
S	The bandwidth usage satisfaction term.
$u_{p_i}(.)$	The utility function of the player. p = A, B or L, which denote Alien, Bill or Linus, respectively.
x_{p_i}	The percentage of the player's bandwidth to be used by himself. p = B, L or AP, which denote Bill, Linus, or any types of AP, respectively. $0 \leq x_{p_i} \leq 1$.
n_p	The number of players who choose to join the service. p = A or LB, which denote Alien or free roamers (Linuses or Bills as SSs), respectively. $n_p \in \aleph$.
C_{p_i}	The costs of the player for maintaining the AP. p = B or L, which denote Bill or Linus, respectively.$C_{p_i} > 0$.
b_{p_i}	The total bandwidth a player has. p = B, L or AP, which denote Bill, Linus, or any types of AP, respectively.$b_{p_i} > 0$.
h_{p_i}	The satisfaction coefficient of the player. p = A, B or L, which denote Alien, Bill or Linus, respectively. $h_{p_i} > 0$.
ϵ_{p_i}	Least bandwidth threshold of the player. p = A, B or L, which denote Alien, Bill or Linus, respectively. $\epsilon_{p_i} \geq 1$.
$h_{p_i} \ln(b_{p_i} x_{p_i})$	The satisfaction term in the player's utility. p = B or L, which denote Bill or Linus, respectively.
Z_{p_i}	The bonus of the player's utility function, the utility of free roaming privilege. p = B or L, which denote Bill or Linus, respectively.$Z_{p_i} > 0$.
P_A	The payment of each Alien. $P_A > 0$.
R	The percentage that the administration allots to Bill from the payment. $0 < R < 1$.
$n_A P_A R$	The payment term of Bill's utility function, the total utility from the Aliens.
k_{L_i}	The sharing coefficient of Linus. $k_{L_i} > 0$.
$k_{L_i} \ln[(1 - x_{L_i}) b_{L_i}]$	The sharing term in Linus's utility.
S_{A_i}	The satisfaction term of Alien.
$\hat{x}_{B_k}$	The particular x_{B_i} that corresponding to a discontinuity point in the utility curve.
$n_{A_{total}}$	The total number of Aliens in the system. $n_{A_{total}} \in \aleph$.

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Utility Function of Bill

As both a bandwidth user and a supplier, Bill optimizes his payoffs by compromising between using and selling his bandwidth. Bill's utility function can be simply determined by four terms: the payment from the Aliens, the costs of maintaining the AP, the satisfaction function of using bandwidth, and the bonus of participating (i.e. when Bill acts as a roaming SS someday, he can access the network freely).

Definition 2 *Suppose a player operates as Bill (AP),* B_i*,* $i \in \aleph$*, the utility function* $u_{B_i}(x_{B_i})$ *is:*

$$u_{B_i}(x_{B_i}) = \begin{cases} n_A P_A R - C_{B_i} + Z_{B_i} & \textit{if}\, b_{B_i} x_{B_i} \leq \epsilon_{B_i} \\ n_A P_A R - C_{B_i} + & \\ h_{B_i} \ln(b_{B_i} x_{B_i}) + Z_{B_i} & \textit{if}\, b_{B_i} x_{B_i} > \epsilon_{B_i}. \end{cases}$$

We denote x_{B_i} as the percentage of Bill's proportion of bandwidth that he keeps to himself, and the first term $n_A P_A R$, thereby, is the payment term. The first term, n_A, is the number of Aliens who choose to join the service, and P_A is the money that each Alien pays for the administration. On the other hand, R is the percentage that the administration allots to Bill from the payment, and the product $n_A P_A R$ is the total profit Bill can receive from selling his bandwidth. In the second term, C_{B_i} denotes the costs of maintaining the AP, and third term is the satisfaction term of bandwidth usage, as it is previously defined. In addition, Bill's total bandwidth is denoted as b_{B_i}, his satisfaction coefficient h_{B_i}, and his minimal bandwidth threshold for meaningful usage ϵ_{B_i}. Note that all the parameters with an "i" suffix denotes that the parameters might differ from different Bills because of their various preferences and applications. We use similar notations in the following parts of this chapter. The percentage of bandwidth Bill allocates to himself is denoted as x_{B_i};

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thus the bandwidth that Bill can use is $b_{B_i}x_{B_i}$. And the last term, Z_{B_i}, is a positive "bonus term," representing the utility of Bills' free roaming privilege. Note that when Bill is not at home, he does not access the internet resources from his own access point, which means the parameter x_{B_i} is set to zero intuitively.

Utility Function of Linus

Similar to Bill, Linus also behaves as both a bandwidth supplier and a user, and has almost the same considerations as Bill; however, since he is an altruist in nature, he has a different sharing term formula from Bill's payment term. The sharing term represents the utility of spiritual payoffs that Linus receives when he shares his bandwidth with others. Therefore, Linus' utility function can also be determined by four terms: the satisfaction function of using bandwidth, the spiritual payoffs from sharing, the costs of maintaining the AP, and the bonus of free roaming privilege.

Definition 3 *Suppose a player operates as Linus (AP), L_i, $i \in \aleph$, the utility function $u_{L_i}(x_{L_i})$ is:*

$$u_{L_i}(x_{L_i}) = \begin{cases} k_{L_i} \ln[(1 - x_{L_i})b_{L_i}] + & \\ Z_{L_i} - C_{L_i} & \text{if } b_{L_i}x_{L_i} \leq \epsilon_{L_i} \\ k_{L_i} \ln[(1 - x_{L_i})b_{L_i}] + & \\ Z_{L_i} - C_{L_i} + h_{L_i} \ln(b_{L_i}x_{L_i}) & \text{if } b_{L_i}x_{L_i} > \epsilon_{L_i}. \end{cases}$$

The meaning of x_{L_i}, b_{L_i}, ϵ_{L_i}, h_{L_i}, C_{L_i}, Z_{L_i} are similar to those of Bill's, and the remaining term is sharing term. We assume that Linus is a generous giver who likes to share with others. This term reflects the utility that Linus gain when he shares $[(1-x_{L_i})b_{L_i}]$ amount of bandwidth. Since the sharing concept is similar to the satisfaction function, it

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is not surprising that their formulation are alike. Likewise, we define k_{L_i} as the sharing coefficient. Note again that in the case of Linus, when Linus is not at home, he does not access the internet resources from his own access point either, which means the parameter x_{L_i} is set to zero intuitively. Since keeping the bandwidth to himself does not benefit him, giving out is obviously the best alternative.

Utility Function of Alien

As a user, Alien has to pay for his wireless access, so what he concerns the most is the quality of connection and the price to pay. As we mentioned, users evaluate their quality of connection according to the satisfaction function. Also note that we assume that all the subscriber stations(including free roamers and Aliens) equally divided the bandwidth, which means a subscriber station in the system receives the same share of bandwidth as others.

Definition 4 *Suppose a player operates as Alien, A_i, $i \in \aleph$, the satisfaction term S_{A_i} is the utility of using $(\frac{b_{AP_i}(1-x_{AP_i})}{n_A+n_{LB}})$ amount of bandwidth allocated by the access point:*

$$S_{A_i} = \begin{cases} 0 & \mathit{if}\ \frac{b_{AP_i}(1-x_{AP_i})}{n_A+n_{LB}} \leq \epsilon_{A_i} \\ h_{A_i}\ln(\frac{b_{AP_i}(1-x_{AP_i})}{n_A+n_{LB}}) & \mathit{if}\ \frac{b_{AP_i}(1-x_{AP_i})}{n_A+n_{LB}} > \epsilon_{A_i}. \end{cases}$$

We denote b_{AP_i} as the total bandwidth that the serving AP (Bill or Linus) has, and x_{AP_i} as the percentage that the AP reserves for his own using. The total shared bandwidth is $b_{AP_i}(1 - x_{AP_i})$. Similar to the previous formulation, h_{A_i} is the Alien's satisfaction coefficient. Note that this coefficient may be different from various Aliens since they may use different type of network applications with different preferences. Furthermore, this coefficient actually determines whether an Alien is choosy or not. That is, an Alien

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with high h_{A_i} is considered less choosy. In our system, the bandwidth is equally shared among all SSs (i.e. Aliens, roaming Linuses, and roaming Bills). The number of Aliens who choose to join the service is denoted as n_A. Similarly, the total number of roaming Linuses and Bills (as roaming users to the serving AP) in the cell is denoted as n_{LB}. The per-user shared bandwidth is thus $\frac{b_{AP_i}(1-x_{AP_i})}{n_A+n_{LB}}$.

The only two possible strategies that Alien can adopt is either join (J) or not to join (NJ), and choosing not to join the game apparently brings zero utility. On the other hand, if Alien chooses to join, the utility function is the satisfaction of using bandwidth minus the payment to the administration, as it is given below.

Definition 5 *Suppose a player operates as Alien, A_i, $i \in \aleph$, with $P_A > 0$ denotes the payment for the network access. The utility denoted by u_{A_i} is:*

$$u_{A_i} = \begin{cases} S_{A_i} - P_A & \textit{if } J \\ 0 & \textit{if } NJ. \end{cases}$$

1.4 Bill versus Aliens Game

Now we formulate Bill versus Alien as a normal form game. On the basis of one AP versus several SSs, we examine the existence of Nash Equilibria in the games of Bills versus Aliens. Bill's strategy is to decide the percentage of his total bandwidth allotting for self using x_{B_i} and the percentage to sell $(1 - x_{B_i})$. Each Alien's strategy is either to join or not to join——when the condition is profitable, he joins; otherwise, not to join. On the other hand, when the condition is not the most profitable for Bill, he tends to change decisions. In other words, Alien can only passively choose to accept the current condition or not; therefore, Bill's decision is the key factor to reach the final equilibrium.

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Note that in our game model, we assume that the parameters are abiding during the game period. Though it is fact that the users' bandwidth needs may vary dramatically over time, our assumption is still legitimate since a player takes longer time to accomplish the desired purpose whereas the decision making changes from time to time in the micro-scale game we discuss. Another important assumption of our game analysis is that all the system parameters are known in the analytic processes. Thus,the analytic solution of Nash Equilibria can be directly determined in theory.

To determine Bill's maximal utility, we compute the first-order derivative of the utility function: $u'_{B_i}(x_{B_i})$:

$$u'_{B_i}(x_{B_i}) = \begin{cases} 0 & \text{if } b_{B_i}x_{B_i} \leq \epsilon_{B_i} \\ \frac{h_{B_i}}{x_{B_i}} & \text{if } b_{B_i}x_{B_i} > \epsilon_{B_i}. \end{cases}$$

Unfortunately, we fail to gain any useful information from this straightforward mathematical analysis since the fixed range of x_{B_i} is from 0 to 1. We could not find the local maximum, let alone the Nash Equilibria. The curve of Bill's utility function versus x_{B_i} consists of a decreasing downward step function ($n_A P_A R$), a logarithmically increasing satisfaction function ($h_{B_i} \ln(b_{B_i}x_{B_i})$), and constant terms. Note that the constant terms are insignificant since their only effect is to shift the curve upward or downward, which has nothing to do with that at what x_{B_i} the maximum appears. And it is intuitive that $n_A P_A R$ is a decreasing downward step function.

When the provided bandwidth meets an Alien's minimal bandwidth threshold, he joins. And once the Alien chooses to join, Bill receives constant profit from the Alien, as the way payment is constant. The profit stays the same until the provided bandwidth no longer satisfies that Alien. Until then, Bill receives zero profits from that Alien.

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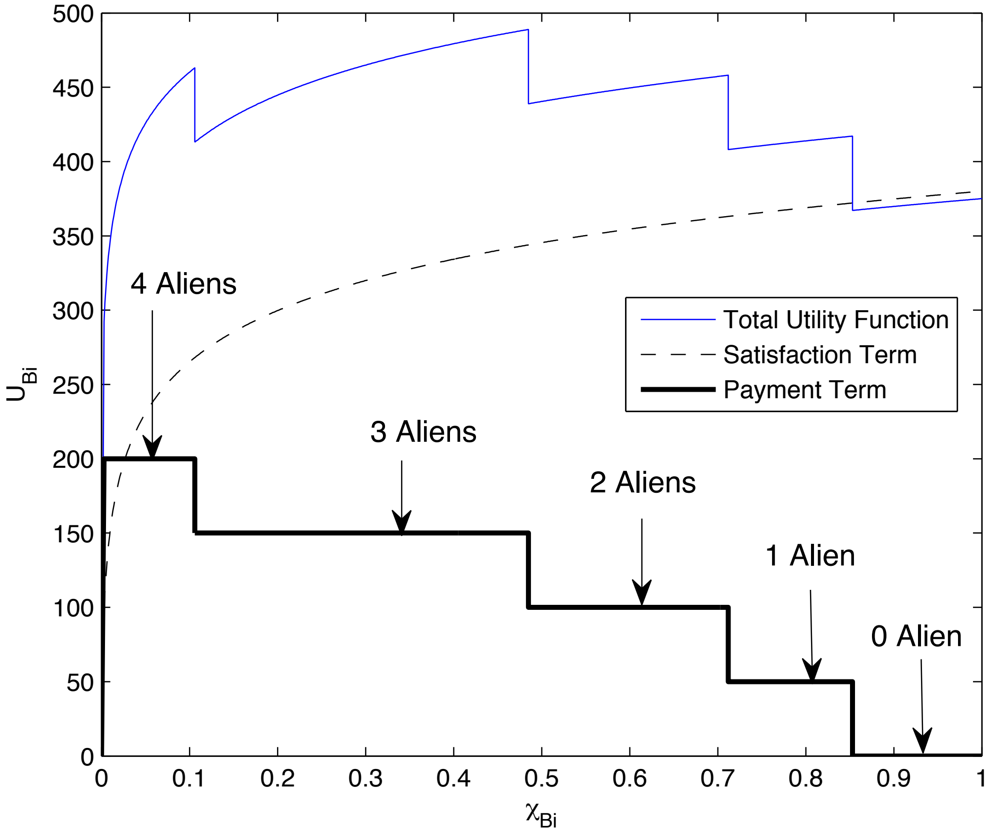

Figure 1.1: Bill's Utility versus the Number of Joining Aliens and x_{B_i}. Bill's Total Utility Function = Satisfaction Term + Payment Term + Constant

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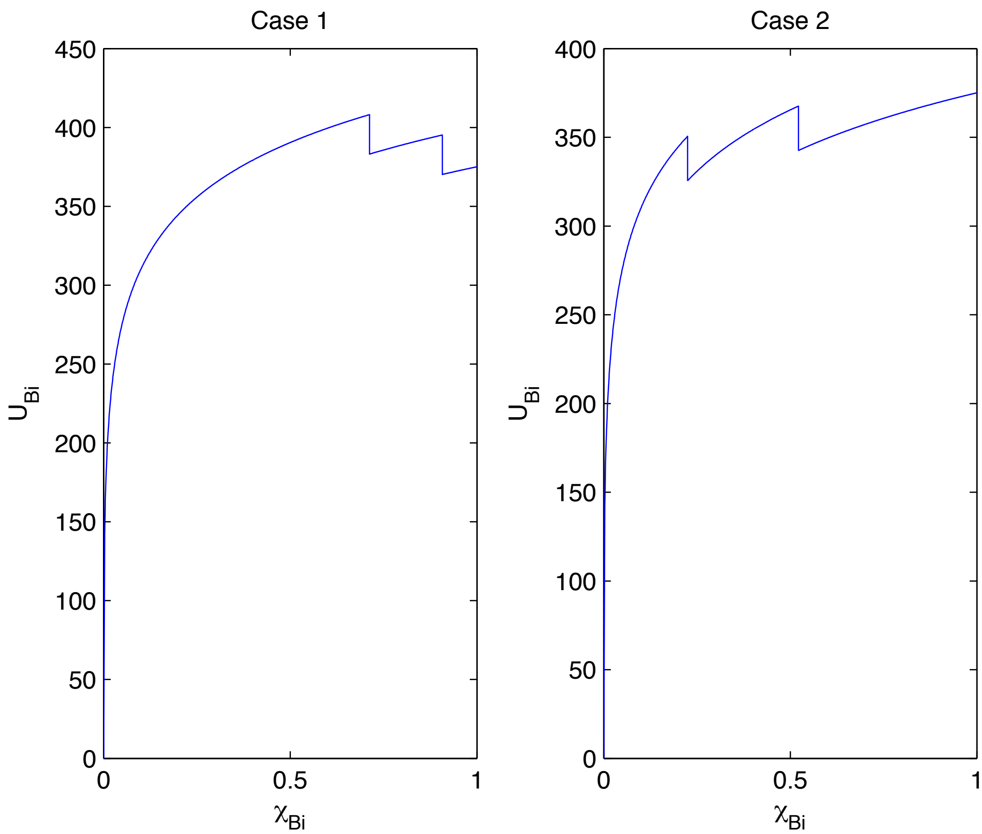

Figure 1.2: Classification of Bill's Utility Function Based on the Property of Local Maximum Points: (a) Case 1 (b) Case2

As shown in Fig. 1.1, we show a general case with 4 Aliens, the dashed line which is logarithmically increasing indicates the satisfaction term, the utility from self using of bandwidth. The lower line is, on the other hand, payment term, the profits gain from the payment of Aliens. As x_{B_i} goes up, the bandwidth for sharing diminishes, and until the bandwidth is too small to satisfy an Alien, he deviates from the system, then the Bill loses one unit of payment. Thus, a single step the payment term drops causes one discontinuity point in the curve. We can see that Bill's utility function (the upmost curve in the graph) is the superposition of the satisfaction term and the payment . The number of discontinuity points is equal to the number of Aliens $n_{A_{total}}$. For example, in the $4-$Alien game in Fig. 1.1, there are 4 local optimums in the utility function.

The location of the discontinuity point is an important factor to decide the maximal

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utility. We can classify the utility curves into two groups as shown in Fig. 1.2(a), Case 1 shows that if the "tail" (i.e. the remaining portion after the discontinuity point to $x_{B_i} = 1$) is too short to force the logarithmic term increase beyond the former local maximum value, one of the discontinuity points. Thus, Bill must adjust x_{B_i} to make the exact number of Aliens join to maximize his utility. To achieve this purpose, Bill's best response is to adjust the number of Aliens to a point where they will choose to join. The optimal point has to be at one of the discontinuity points, which are denoted as $\hat{x}_{B_k}, k \in [1, n_{A_{total}}]$. When $(1 - x_{B_i})$ overtakes these values, the payment term then stops raising and the satisfaction term decreases, thereby decreasing the overall utility. Case 2 of Fig. 1.2(b) shows that the tail of the utility curve is long enough to exceed the value of the former local maximum. Seemingly, the global maximum appears at the boundary point, $x_{B_i} = 1$ (i.e. Bill uses all the bandwidth himself). Hence, Aliens refuse to join as it is out of service.

Also note that there also exists a curve which can be divided into both Case 1 and 2. That is, the value of the middle maximal point has an identical value to the tail. Thus, in such cases, Bill have identical and maximal utility profile at these points. Since it does not make any difference for Bill to choose between these points, Bill will randomly choose among these maximal points. Nevertheless, in any cases from above three categories, each player has chosen his strategy and no player can benefit by changing his strategy unilaterally. So our current set of strategy choices and the strategy set reaches a Nash Equilibrium. Note that since Bill can maximize his strategy in this Nash Equilibrium, we can infer that if any user deviate from their best response in the Nash Equilibrium profile, the utility of Bill will be hurt, so the Nash Equilibrium itself also serve as a Pareto optimal solution.

Assume that $n_{A_{total}}$ Aliens are in the game and sorted by h_{A_i} in an ascending order

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such that $h_{A_i} \leq h_{A_j}$, for any $i < j$. From the definition of h_A, A_j has greater satisfaction than A_i under the same sharing setting. If A_i joins the service, then A_j joins. But it is not necessarily true in contrast. Note that since A_i joins, $A_{i+1}, A_{i+2}, ..., A_{n_{A_{total}}}$ also join. When A_i joins but A_{i-1} does not, the number of joining Aliens is $n_A = n_{A_{total}} - i + 1$.

Corollary 1 ***(Best Response of Alien)*** *Alien A_i chooses to join (J) when inequality (1.1) holds; otherwise, A_i chooses NJ.*

$$u_{A_i} = h_{A_i} \ln(\frac{b_{B_i}(1 - x_{B_i})}{n_A + n_{LB}}) - P_A \geq 0$$

and

$$\frac{b_{B_i}(1 - x_{B_i})}{n_A + n_{LB}} > \epsilon_{A_i}$$

$$\Rightarrow x_{B_i} \leq min\{(1 - \frac{n_A + n_{LB}}{b_{B_i}} e^{\frac{P_A}{h_{A_i}}}), (1 - \frac{\epsilon_{A_i}(n_A + n_{LB})}{b_{B_i}})\} \tag{1.1}$$

In the Bill versus Alien game, the best response of Bill is to maximize his utility function u_{B_i}. As illustrated in Fig. 1.2, the global optimum is among one of the several local maximum points $(\hat{x}_{B_k}, u_{B_i}(\hat{x}_{B_k}))$, or at the boundary point $(x_{B_i}, u_{B_i}) = (1, u_{B_i}(x_{B_i} = 1))$, where:

$$\hat{x}_{B_k} = min\{(1 - \frac{n_A + n_{LB}}{b_{B_i}} e^{\frac{P_A}{h_{A_i}}}), (1 - \frac{\epsilon_{A_i}(n_A + n_{LB})}{b_{B_i}})\}.$$

As shown in Fig. 1.2, we denote the $k-$th local optimum from the left as $(\hat{x}_{B_k}, u_{B_i}(\hat{x}_{B_k}))$,

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where Bill maximizes x_{B_i} but still attracts totally $n_{A_{total}} - k + 1$ Aliens (i.e. A_k, A_{k+1},..., $A_{n_{A_{total}}}$) to join.

The global maximum of Bill's utility is:

$$u_{B_i}(x^{\star}_{B_k}) = max_{k \in [1, n_{A_{total}}]} \{u_{B_i}(\hat{x}_{B_k}), u_{B_i}(1)\}.$$

Corollary 2 ***(Best Response of Bill)*** *Bill's best response is choosing $x_{B_i} = x^{\star}_{B_k}$ from (1.2) to maximize his utility, where:*

$$x^{\star}_{B_k} = argmax_x \{u_{B_i}(\hat{x}_{B_k}), u_{B_i}(1)\} \tag{1.2}$$

From the previous discussion, it is obvious that the best response is to find the global optimum of Bill's utility. Note that $x^{\star}_{B_k}$ is also the best response as all other possible $u_{B_i}(x_{B_i})$ values are dominated by $u_{B_i}(x^{\star}_{B_k})$.

Proposition 1 ***(Nash Equilibrium: Bill v.s. Alien)*** *In the Nash Equilibrium, Bill uses $x^{\star}_{B_k}$ percent of his own bandwidth and offers $(1 - x^{\star}_{B_k})$ to Aliens. Alien i joins the service when h_{A_i} satisfies inequality (1.1) holds; otherwise, he does not join.*

Proof:

As all players in a game choose their best responses respectively, no player will unilaterally deviate from the operating point, and thereby achieving a Nash Equilibrium. From Corollary 1 and 2, we derive the Nash Equilibrium in Bill v.s. Alien game. $x^{\star}_{B_k}$ in (1.2) is Bill's best response. After $x^{\star}_{B_k}$ is determined, by sorting parameter h_{A_i}, Aliens' strategy set is determined.

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1.5 Linus versus Aliens Game

Similar to Bill, Linus has to allot his total bandwidth to the portion he reserves for himself, x_{L_i}, as well as the portion he decides to share with others equivalently, $(1 - x_{L_i})$. To find the optimal value of the utility, we take the first and second order derivatives of $u_{L_i}(x_{L_i})$:

$$u'_{L_i}(x_{L_i}) = \begin{cases} \frac{-k_{L_i}}{1-x_{L_i}} = \frac{k_{L_i}}{x_{L_i}-1} & \text{if } b_{L_i}x_{L_i} \leq \epsilon_{L_i} \\ \frac{(k_{L_i}+h_{L_i})x_{L_i}-h_{L_i}}{x_{L_i}(x_{L_i}-1)} & \text{if } b_{L_i}x_{L_i} > \epsilon_{L_i}. \end{cases}$$

$$u''_{L_i}(x_{L_i}) = \begin{cases} \frac{-k_{L_i}}{(x_{L_i}-1)^2} & \text{if } b_{L_i}x_{L_i} \leq \epsilon_{L_i} \\ \frac{-h_{L_i}(x_{L_i}-1)^2-k_{L_i}x_{L_i}^2}{x_{L_i}^2(x_{L_i}-1)^2} & \text{if } b_{L_i}x_{L_i} > \epsilon_{L_i}. \end{cases} \tag{1.3}$$

Now, we derive the Nash Equilibrium in operating region with meaningful bandwidth usage (i.e. $b_{L_i}x_{L_i} > \epsilon_{L_i}$ and Linus has non-zero utility). To find the maximum of utility function, the first order derivative equals to 0 and the second negative.

Corollary 3 ***(Best Response of Linus)*** *When $b_{L_i}x_{L_i} > \epsilon_{L_i}$, to find the best response that maximizes Linus' utility, we have:*

$$u'_{L_i}(x_{L_i}) = \frac{(k_{L_i}+h_{L_i})x_{L_i}-h_{L_i}}{x_{L_i}(x_{L_i}-1)} = 0$$

$$\Rightarrow x_{L_i} = \frac{h_{L_i}}{k_{L_i}+h_{L_i}}. \tag{1.4}$$

In accordance with (1.4), Linus' best response is to set bandwidth usage ratio x_{L_i}. From (1.3), $u''_{L_i}(x_{L_i}) < 0$ is always true in operating region with meaningful bandwidth

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usage (i.e. $b_{L_i}x_{L_i} > \epsilon_{L_i}$). Linus has the maximal utility with x_{L_i} given in (1.4). Unlike the Bill game, $u_{L_i}(x_{L_i})$ is independent of the number of joined Aliens n_A. In other words, Linus' best response x_{L_i} is similarly regardless of Aliens' strategies. Thus, setting x_{L_i} to the optimal value in (1.4) is also the best response for Linus.

Corollary 4 ***(Best Response of Alien)*** *Alien A_i chooses to join (J) when inequality (1.5) holds; A_i chooses NJ, otherwise.*

$$u_{A_i} = h_{A_i} \ln(\frac{b_{L_i}(1 - x_{L_i})}{n_A + n_{LB}}) - P_A \geq 0$$

and

$$\frac{b_{L_i}(1 - x_{L_i})}{n_A + n_{LB}} > \epsilon_{A_i}$$

$$\Rightarrow x_{L_i} \leq min\{(1 - \frac{n_A + n_{LB}}{b_{L_i}} e^{\frac{P_A}{h_{A_i}}}), (1 - \frac{\epsilon_{A_i}(n_A + n_{LB})}{b_{L_i}})\} \quad (1.5)$$

Proposition 2 ***(Nash Equilibrium I: Linus v.s. Alien)*** *When $b_{L_i}x_{L_i} > \epsilon_{L_i}$, Linus uses $\frac{h_{L_i}}{k_{L_i}+h_{L_i}}$ percent of his bandwidth in the Nash Equilibrium. All Aliens, when inequality (1.6) holds, will join the service; otherwise, they will not.*

$$\frac{h_{L_i}}{k_{L_i} + h_{L_i}} \leq min\{(1 - \frac{n_A + n_{LB}}{b_{L_i}} e^{\frac{P_A}{h_{A_i}}}), (1 - \frac{\epsilon_{A_i}(n_A + n_{LB})}{b_{L_i}})\} \quad (1.6)$$

Proof:

As *Corollary 3* states, x_{L_i} in (1.4) shows the best response of Linus. Regardless of

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Aliens' actions, Linus is fixed to the set $x_{L_i} = \frac{h_{L_i}}{k_{L_i}+h_{L_i}}$, which implies that Linus has no incentive to deviate from the equilibrium. Substitute $x_{L_i} = \frac{h_{L_i}}{k_{L_i}+h_{L_i}}$ in (1.5), an Alien's best response and the inequality condition (1.6) is then derived. With both Linus and Aliens making their best choices, the Nash Equilibrium is then reached. On the other hand, since (1.4) gives a unique solution and all parameters in (1.6) stay constant to a given set of players, this Nash Equilibrium is then unique.

Proposition 3 ***(Nash Equilibrium II: Linus v.s. Alien)*** *When $b_{L_i}x_{L_i} \leq \epsilon_{L_i}$, the condition that Linus sets $x_{L_i} = 0$ and shares all of his bandwidth at the Nash Equilibrium. Aliens, when inequality (1.7) holds, will join the service; otherwise, they will not join.*

$$0 \leq min\{(1 - \frac{n_A + n_{LB}}{b_{L_i}} e^{\frac{P_A}{h_{A_i}}}), (1 - \frac{\epsilon_{A_i}(n_A + n_{LB})}{b_{L_i}})\} \tag{1.7}$$

Proof:

When $b_{L_i}x_{L_i} \leq \epsilon_{L_i}$, since $u'_{L_i}(0) = 0$ and $u''_{L_i}(0) = -k_{L_i} < 0$, Linus has the maximal utility at $x_{L_i} = 0$. We can then conclude that the setting $x_{L_i} = 0$ is his best response. Since when $b_{L_i}x_{L_i} \leq \epsilon_{L_i}$, Linus does not benefit from keeping the bandwidth to himself, namely, failing to get any payoffs from the satisfaction term, he will then certainly share all of his bandwidth. Similar to the previous case, by substituting $x_{L_i} = 0$ in (1.5), an Alien's best response and inequality condition (1.7) are then derived.

1.6 Practical Protocol Design

In this section, we illustrate the ways to practically achieve the theoretic results in the cooperative wireless networks. We have derived the theoretic Nash Equilibria of Linus-

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Aliens game and Bill-Aliens game previously, and also prove that when system parameters are all known, the Nash Equilibria is then readily determined. Nevertheless, in real-world systems, Aliens' system parameters remain unknown to the access points, and so do the access points' and other Aliens' system parameters to the Aliens. In response to that, an ideal protocol should be able to achieve Nash Equilibrium convergence based on available information in a practical system operation.

To simplify, the mobility of Aliens is modeled as two separate events: leaving one cell and joining other cells. As the mobility problem could be decoupled, we can focus our discussion on the interactions between the players within a single cell. In addition, from the theoretic analysis stated in the previous section, the best response of Linus is irrelevant to Aliens' strategies; therefore, the choices of Aliens have no bearings on the Nash equilibrium. On the other hand, since Linus always sets the bandwidth usage ratio to $\frac{h_{L_i}}{k_{L_i}+h_{L_i}}$, Aliens then react accordingly. The dynamics in the Linus-versus-Aliens game is trivial, so we only discuss the Bill-Aliens game here. Other than that, we also provide a practical protocol that reaches to the steady state; namely, the Nash equilibrium.

In the Bill-versus-Aliens game, Bill is the leader and Aliens are the followers. Bill selects the optimized strategy to maximize his utility, and Aliens will then adjust their best response according to Bill's selected strategy (quantity of the offered bandwidth). Moreover, Bill's strategy $x^{\star}_{B_k}$ in the Nash equilibrium leads to the global optimum of Bill's utility $u^{\star}_{B_k}$. Similarly, Linus-versus-Aliens game is also a leader-follower game. Linus also has the maximal utility in the Nash equilibrium. The optimality of the game equilibria is desirable since Bill and Linus both maximize their utility functions by setting up the access points and sharing their bandwidth. As a result, the optimal theoretic equilibrium and the corresponding practical implementation algorithm can facilitate the healthy growth

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of cooperative WiFi wireless access point deployment.

Algorithm: Finding Bill's Best Response x_{B_i}

Initialize $bool\_stop \leftarrow 0,\ \Delta \leftarrow 0$
Initialize $x_{max} \leftarrow 0,\ n_{max} \leftarrow n_A(x_{B_i} = 0)$
Initialize $lower \leftarrow 0,\ upper \leftarrow 1$
Initialize $x_{B_i}(t) \leftarrow 0$
While $bool\_stop = 0$
  $if\ \Delta = 0$
    While $(upper - lower) \geq \xi$
      Execute **Algorithm:Binary Search**
    End While
    Execute **Algorithm:Update Maximum**
    $\Delta \leftarrow \Delta + 1$
    $x_{B_i}(t) \leftarrow x_{max} \cdot exp(\Delta \cdot P_A \cdot R/h_{B_i})$
    $if\ x_{B_i}(t) \geq 1$
      $x_{B_i}(t) \leftarrow x_{max}$
      $bool\_stop \leftarrow 1$
  $elseif\ \Delta > 0$
    $if\ (u_{B_i}(t-1)) \geq u_{max}$
      $lower \leftarrow x_{B_i}(t-1)$
      $upper \leftarrow 1$
      $x_{B_i}(t) \leftarrow (upper + lower)/2$
      $\Delta \leftarrow 0$
      $n_{max} \leftarrow n_A(t-1)$
    $elseif\ (u_{B_i}(t-1)) < u_{max}$
      $\Delta \leftarrow \Delta + 1$
      $x_{B_i}(t) \leftarrow x_{max} \cdot exp(\Delta \cdot P_A \cdot R/h_{B_i})$
      $if\ x_{B_i}(t) \geq 1$
        $x_{B_i}(t) \leftarrow x_{max}$
        $bool\_stop \leftarrow 1$
End While
Return x_{max}

Figure 1.3: Algorithm to Find Bill's Best Response x_{B_i}

1.6.1 Algorithm Design

Since all the players strive to maximize their payoffs, a steady state will appear when Bill achieves the maximum of his utility. When Bill keeps his behavior unchanged, the only thing Aliens can do rationally is to react in their best response accordingly. In other words, once Bill adopts his optimal strategy, Aliens will have no better strategy than remaining in

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Algorithm:Binary Search

$if\ n_A(t-1) = n_A(t-3)$
  $if\ u_{B_i}(t-1) \geq u_{B_i}(t-3)$
    $lower \leftarrow x_{B_i}(t-1)$
  $else$
    $upper \leftarrow x_{B_i}(t-1)$
$elseif\ n_A(t-1) > n_A(t-3)$
  $if\ n_A(t-1) = n_{max}$
    $lower \leftarrow x_{B_i}(t-1)$
    $upper \leftarrow x_{B_i}(t-3)$
  $else$
    $upper \leftarrow x_{B_i}(t-1)$
$elseif\ n_A(t-1) < n_A(t-3)$
    $upper \leftarrow x_{B_i}(t-1)$
$x_{B_i} \leftarrow (upper + lower)/2$

Figure 1.4: Algorithm: Bill Computes The Local Maximum of Utility Function With Binary Search

their current situation, and thus the set of strategy choices and the corresponding payoffs constitute a Nash Equilibrium. Also note that the Aliens are not tend to deliberately tell a falsehood for getting higher payoffs in the next round of our model. Precisely, if Aliens give answers that contradict to the truth, in most cases, he might receive nothing in the next round. Also, in the contrary case, it is impossible for one rational Alien to accept an unacceptable condition. Thus, it is apparent that our focus is on how Bill determines x_{B_i}.

To find Bill's optimal strategy, we should try to find the maximum value in Bill's utility function. The goal of our algorithm design is to compute the optimal bandwidth usage ratio x_{B_i} that leads to the global maximum of Bill's utility function. As discussed in Section 3, the global optimum in the utility curve (similar to the ones illustrated in Fig. 1.1 and 1.2), are among one of the local optimums, namely, discontinuity points $\hat{x}_{B_k}$, or the boundary point $x_{B_i} = 1$ among $n_{A_{total}}$ discontinuity points.

Bill can compute his maximum utility by adopting a naive brute force method that ranges from $x_{B_i} = 0$ to $x_{B_i} = 1$ with a step size ξ, which is, however, impractical and

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Algorithm: Update Maximum

$x_{max} = (upper + lower)/2$
  $if\ n_A(t-1) > n_A(t-3)$
    $u_{max} \leftarrow u_{B_i}(t-1)$
    $n_{max} \leftarrow n_A(t-1)$
  $elseif\ n_A(t-1) < n_A(t-3)$
    $u_{max} \leftarrow u_{B_i}(t-3)$
    $n_{max} \leftarrow n_A(t-3)$
  $elseif\ n_A(t-1) = n_A(t-3)$
    $if\ u_{B_i}(t-1) \geq u_{B_i}(t-3)$
      $u_{max} \leftarrow u_{B_i}(t-1)$
      $n_{max} \leftarrow n_A(t-1)$
    $else$
      $n_{max} \leftarrow (n_A(t-1) + 1)$
      $u_{max} \leftarrow \{h_{B_i} \ln(b_{B_i} x_{max}) + n_{max} P_A R$
        $-C_{B_i} + Z_{B_i}\}$

Figure 1.5: Algorithm: Update the Temporarily Maximum Values x_{max}, u_{max} and n_{max}

inefficient. Since when the step size ξ is too large, we can barely find a local maximum, let alone the global maximum utility. On the other hand, if the step size is too small, it is also considered inefficient since it can never reach the steady state before an Alien joins or leaves the system. Therefore, we need to introduce another protocol that is practical and efficient.

The basic idea of the proposed algorithm is to find the global optimum by smartly adjusting x_{B_i}. Although Aliens' parameter is invisible to Bill, the number of potential joined Aliens at a given x_{B_i} is observable and thereby helping Bill to estimate the current situation to make the best choice. As shown in Fig. 1.1, the utility function is the sum of a decreasing ladder-shaped term due to the dropping number of Aliens (i.e. the payment term) and a rising logarithmic term (i.e. the satisfaction term). The discontinuity point $\hat{x}_{B_k}$ surely is the local optimum, and the global optimum must be among these points or at the point of $x_{B_i} = 1$.

Observation 1 *If a better bandwidth usage strategy $x^{\dagger}_{B_i}$ leads to a greater utility $u_{B_i}(x^{\dagger}_{B_i})$*

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than the utility of the current strategy x_{B_i}, the inequality (1.8) holds:

$$u_{B_i}(x^{\dagger}_{B_i}) \geq u_{B_i}(x_{B_i}) \ \Rightarrow n^{\dagger}_{A} P_A R - C_{B_i} + h_{B_i} \ln(b_{B_i} x^{\dagger}_{B_i}) \geq$$

$$n_A P_A R - C_{B_i} + h_{B_i} \ln(b_{B_i} x_{B_i})$$

$$\Rightarrow x^{\dagger}_{B_i} \geq x_{B_i} e^{\frac{P_A R (n_A - n^{\dagger}_A)}{h_{B_i}}} \tag{1.8}$$

where $n^{\dagger}_A$ is the number of joining Aliens when $x^{\dagger}_{B_i}$ is used.

Here we denote the $i-$th local optimum as $\hat{x}_{B_i}$. If we plan to search local optimal values of x_{B_i} from small to large in $x \in [0, 1]$, then we observe that the next $(i+1)$th local optimum $\hat{x}_{B_{i+1}}$ is at least greater than or equal to $\hat{x}_{B_i} \cdot exp(P_A R / h_{B_i})$. This can be explained by the relationship between Bill's utility function and the ladder-shaped payment term, as illustrated in Fig. 1.1. Based on this observation, we can narrow down the x_{B_i} domain to be searched in the proposed algorithm. If we set $\Delta = n_A - n^{\dagger}_A$, the $(i + \Delta)$th local optimum $\hat{x}_{B_{i+\Delta}}$ is at least greater than or equal to $\hat{x}_{B_i} \cdot exp(\Delta \cdot P_A \cdot R / h_{B_i})$.

Fig. 1.3 depicts the main algorithm for searching x_{B_i} best response. Bill gradually amends his strategy according to the observed information (the number of joined Aliens) in each round. The Algorithms in Fig. 1.4 and 1.5 are used by the main algorithm. Fig. 1.4 describes the binary search subroutine to find the local optimum, and Fig 1.5 describes the algorithm that updates the temporarily maximum values after a local optimum is found.

The binary search method is used to narrow down the interval, where a local optimum $\hat{x}_{B_k}$ exists. The bandwidth usage ratio at time t is denoted as $x_{B_i}(t)$, and the corresponding utility is $u_{B_i}(t)$. The number of joined Aliens at t is denoted as $n_A(t)$. The Bill's

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parameters in the previous two tests (i.e at time= $t-1$ and $t-3$) are stored for the binary search computation.

Similarly, among all the visited local optimums, the global maximum values are stored as x_{max}, u_{max}, and n_{max} respectively. The maximum values are initialized with $x_{max}=0$ as the finding process starts from 0 toward 1. The initial value of n_{max} is set to the number of joined Aliens when Bill shares all his bandwidth (i.e. $x_{B_i}=0$).

A discontinuity point $\hat{x}_{B_k}$ is where an Alien changes his mind from joining to not joining. When Bill observes that the joining number of Aliens is different in the two adjacent tests, he knows that the point of local optimum must exist in the close interval between these two adjacent test points. The difference in the number of joining Aliens is denoted as Δ. When $\Delta=0$, the main algorithm applies iterative binary search method (Line $7-9$ and Fig. 1.4) to find an unvisited $\hat{x}_{B_k}$ between the logarithmic segments. We start finding $\hat{x}_{B_k}$ from left to right. When a local optimum is found, Δ is increased, and is used to jump to the right to another un-searched logarithmic segment of utility curve for next round's local optimum searching. The best response finding process starts from the left and jumps to the right to find another local optimum until all local optimums are visited. The main algorithm uses flag value $bool\_stop$ to stop the finding process.

We apply the iterative binary search method to get a local optimum (Line $7-9$), then apply the "jump method" (Line $17-28$) to find other possible local optimums until all x_{Bi} domain is searched. We range the interval between a lower bound $lower$ and a upper bound $upper$ over the x_{B_i} domain. We update $upper$ and $lower$ in each iteration, as described by the binary search algorithm in Fig. 1.4. The binary search iterations stop when the interval is smaller than the accuracy threshold ξ (Line 7).

After a local optimum is found (and set $\Delta>0$), based on what we have observed in

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Observation 1, we apply the term in (1.8) to "jump" to an un-searched x_{B_i} domain (Line 12 and Line 25) to start another round of local optimum searching. When $\Delta > 0$ (Line 16), which implies that an x_{B_i} jumping just occurs at $(t-1)$, then we need to reset the searching interval. On the other hand, if the new utility $u_{B_i}(t-1)$ is greater than u_{max} the maximal values among all previously visited local optimum, the utility curve is similar to the Case 2 in Fig. 1.2, then we should search toward the right part of the logarithmical element and reset $lower$ and $upper$ accordingly (Line $18-20$). If the new utility $u_{B_i}(t-1)$ is less than u_{max}, the utility curve is similar to the Case 1 in Fig. 1.2. Then we should jump again (Line $24-25$). Line $13-15$ and Line $26-28$ check whether all x_{B_i} domain has been searched (i.e. search location $x_{B_i}(t)$ moves to the right and exceeds the domain bound $x_{Bi} \geq 1$), and stop the finding process if necessary.

With binary search iterations, we can find local optimums and compute u_{max}, the optimal utility until now, and the corresponding parameters u_{max} and n_{max}. Use this iterative method to update u_{max} and x_{max} until the whole finding process is completed, we will then get the final u_{max} and x_{max}, which are the global optimum of the utility function and Bill's best response respectively.

Proposition 4 *The proposed search algorithms will result in globally optimal strategies.*

Proof:

As described above, those local optimal strategy points are discrete and distributed in the strategy space, as these x_{B_i} values corresponding to peak locations in Fig. 1.1.

Since location of these local optimal points can be predicted, as described in inequality (1.1), we can find globally optimal strategy by the following procedures:

1. Find a local optimal strategy x_{B_i} as " known' best strategy.

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2. Use the known best strategy to predict and check the location, in which a better strategy may exist.

3. Compare those known local strategy and select the best one as known best strategy.

4. Repeat 1 $\sim$ 3 until all strategy space is checked.

To find local maximum of a single variable function, Golden search, Fibonacci search and binary search are well-known one-order methods. However, they can only be applied for uni-modal function, which monotonically increasing for $x \geq m$ and monotonically decreasing for $x \geq m$ for a specific m in a domain space. To apply these methods into our algorithm, we divide AP's utility function into several segments according to number of users joining the network. To be specific, the joint region of the two segments of n users and n+1 users joining, with a unique local maximum at the discontinuity joint point, can be seen a quisi-unimodal function. In other words, we check these discontinuity points between neighboring segments to find optimal strategy. Therefore, by checking local point of each set of two neighboring segments, Golden search, Fibonacci search and binary search can be applied to find the local optima. Note that the three well-known algorithms have the same average time complexity of $O(\log(n))$.

1.6.2 Protocol Design

After describing the algorithms, we are now demonstrating how our algorithm works in the real-world system. Our algorithms are designed in the case that more or equal Aliens in the system than the number of those who would be theoretically potential to join in light of the access point. Furthermore, our algorithms can resolve the problem when several unknown user private information involved. Nevertheless, in the real-world system, some

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information is visible to access points, like the number of Aliens trying to connect, so we design our algorithms exclusively for the conditions with non-zero Aliens. Therefore, if we consider a extreme system with zero Aliens, since the condition can be aware by the access points, Bill would conclude that the optimal bandwidth usage ratio is 1 immediately. After describing the applications of our algorithms, we move on to highlight the incorporation between our algorithms with real-world systems.

To incorporate the proposed algorithm, we consider each two units of t (as mentioned in our mechanism) as a round trip signaling. In each round trip signaling, the AP sends each user signaling, which contains (1) the bandwidth to provide (2) sequence number X, and each user replies an ACK to tell the AP whether he can accept the suggested amount of bandwidth last round. By gathering the feedback from users' ACK each round, the AP can trace users' behavioral patterns. Then, based on the derived information, he makes a decision and starts the next round trip signaling. Detailed decision procedures are described in the algorithm design.

In each round of the ask-and-reply procedures, users merely express their will without paying anything. Until the end of the ask-and-reply procedures when Bill finds out his optimal operating point, users are then charged for the service. In other words, our mechanism proposes a set of ask-and-reply procedures, which can derive optimal strategy for AP with little signaling overheads. Since signaling takes less time to finish, the proposed protocol is adaptive to dynamic and time-varying network scenarios. More details about time of round trip signaling is then discussed in the following section.

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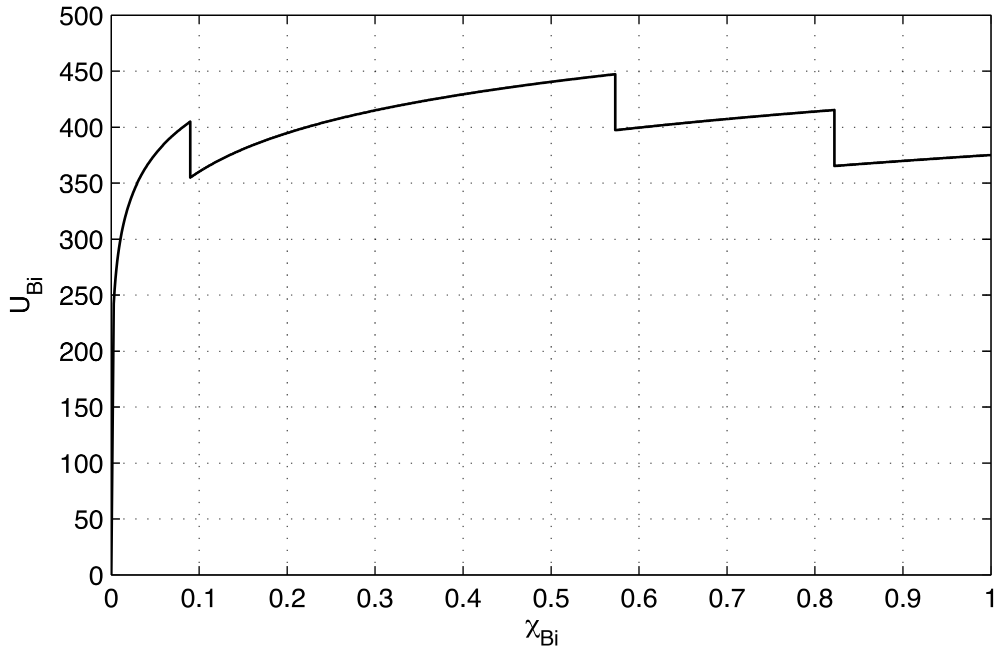

Figure 1.6: Utility Function from Brute Force Method

1.7 Performance Evaluation

As mentioned in protocol design, two units of t stand for round trip signaling time, we use t as time unit here to evaluate bandwidth-sharing efficiency, including Convergence to Equilibrium and Convergence Time.

1.7.1 Convergence to Equilibrium

To evaluate the efficiency and practicality of the proposed protocol implementation, we come up with a discrete-time simulator to simulate the proposed protocol. Compared to the theoretic optimal value, the operational steady state is impractical to implement in real system. The optimal solution, then, is based on brute force method, choosing x_{B_i} from 0 and gradually increases x_{B_i} by adding $\xi = 0.001$. First, we draw a simple example to demonstrate the dynamics and the convergence of the game. More simulation runs and observations are then given in the forth-coming sub-sections. In this example, there

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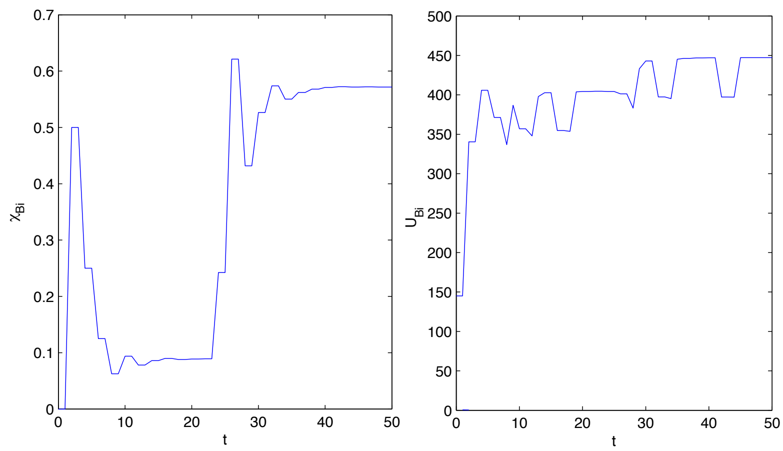

Figure 1.7: Convergence of Bill's (a) Strategy and (b) Utility

are one Bill as AP, three Aliens with different preferences as SSs, and one Linus or Bill as free roaming SS in the simulation scenario. We set the coefficients: $P_A = 100$, and the satisfaction coefficients for the three Aliens are thereby $h_{A_1} = 16.5$, $h_{A_2} = 18$, and $h_{A_3} = 19$, we can see that the first Alien is the most choosy user, but since their demands are roughly similar, it is normal that they share similar coefficient values. We also have $h_{B_i} = 50$, $b_{B_i} = 2000$, $R = 0.5$, and $C_{B_i} = 5$.

The utility function computed by brute force method is given in Fig. 1.6. The results are as we predicted earlier. The discontinuity points are the results from the changing number of joined Alien players. Each discontinuity point indicates one Alien chooses NJ when Bill increases his own bandwidth utilization. That is, the leftmost discontinuity point implies that the first Alien, the most picky one, with $h_{A_1} = 16.5$, chooses NJ while the other two still choose J. And the middle point indicates that the second Alien, with $h_{A_2} = 18$, chooses NJ and the one with $h_{A_3} = 19$ remains his original choice. At the rightmost point, the last Alien chooses NJ, and no Aliens stay in the system. The values of x_{B_i} in those discontinuity points can be calculated by the method we described in the previous section.

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The simulation results of the proposed protocol are given in Fig. 1.7, and 1.8. In Fig. 1.7(a), we only pass through two big pulses and then converge to the steady state rapidly. The steady state x_{B_i} matches the optimal solution computed with brute force method, which is also the theoretic x_{B_i} solution in Nash equilibrium given by (1.2). In Fig. 1.7(b), we can show the utility u_{B_i} of the proposed strategy implementation. Since we apply a binary approach to approximate the steady state, the curve oscillates with smaller amplitude to approach a stable state, and the simulated steady state u_{B_i} result matches the theoretic value in the Nash equilibrium. Note that u_{B_i} steady state is the same as the global maximum in Fig. 1.6. Compared with the brute force method, it takes less time to reach the Nash equilibrium. Furthermore, if we relax the precision restriction to a scale that is acceptable in real life, we can reduce the time cost to about $1/250$. In Fig. 1.6, every x_{B_i} increment is 0.001 and takes 1000 brute force iterations to scan. Contrast to that, our proposed implementation takes much less iterations.

In Fig. 1.8, we contrast the utility variation of the free roamer (Bill or Linus as SS), u_{LB_i}, with the utilities u_{A_i} of Aliens sharing the same access point. We can see in Fig. 1.8(a), the utility of the free roamer stays around a certain level because the free roamer always joins for free services. In Fig. 1.8(b), as we expected, the most choosy Alien, A_1 finally decides his best response, NJ, while the others still remain in the game. Then, when an Alien's utility function equals to zero, the Alien will no longer join the service. The oscillation indicates the joining and leaving behavior of Aliens when Bill is adjusting his bandwidth sharing ratio. We observe that Bill's binary searching on x_{B_i}, as described in Fig. 1.4, dominates the utility and the behaviors of Aliens. We can see that sometimes negative utility emerges since an Alien has to pay for the service in the beginning of a round. When the shared bandwidth is not enough and the payment reaches its sunk cost,

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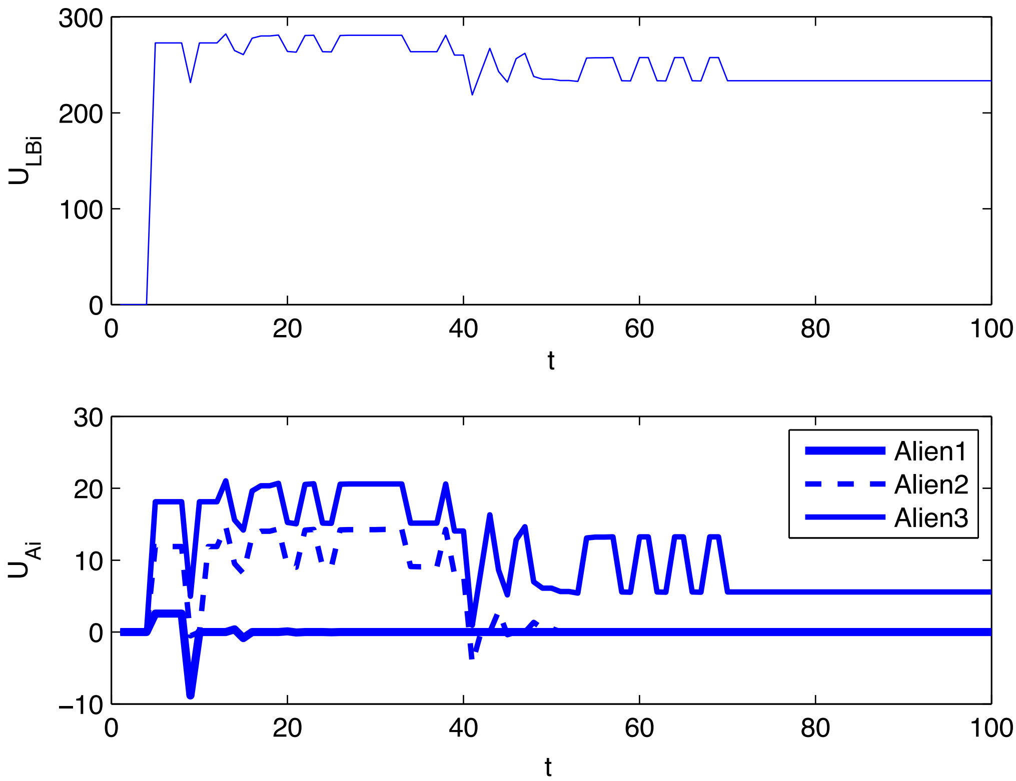

Figure 1.8: Convergence of the Utility and Strategy of (a) Free Roamer (Bill or Linus as SS) and (b) Aliens

the utility becomes negative, and the Alien no longer joins. As a matter of fact, when $u_{A_i} > 0$, they choose J; otherwise, NJ. We can observe that the degree of oscillation in u_{A_i} is negatively correlated with h_{A_i}. As Bill's strategy stabilizes, the degree of oscillation becomes smaller. Compare u_{A_i} to u_{LB_i}, their oscillation tendency are about the same since they equally share the same bandwidth. However, if more users access (i.e. less bandwidth to be shared), their utilities decline as expected, and vice versa. Note that the amplitude of oscillation of the free roamer is much smaller than the Aliens because he is less choosy than the Aliens as his access is free.

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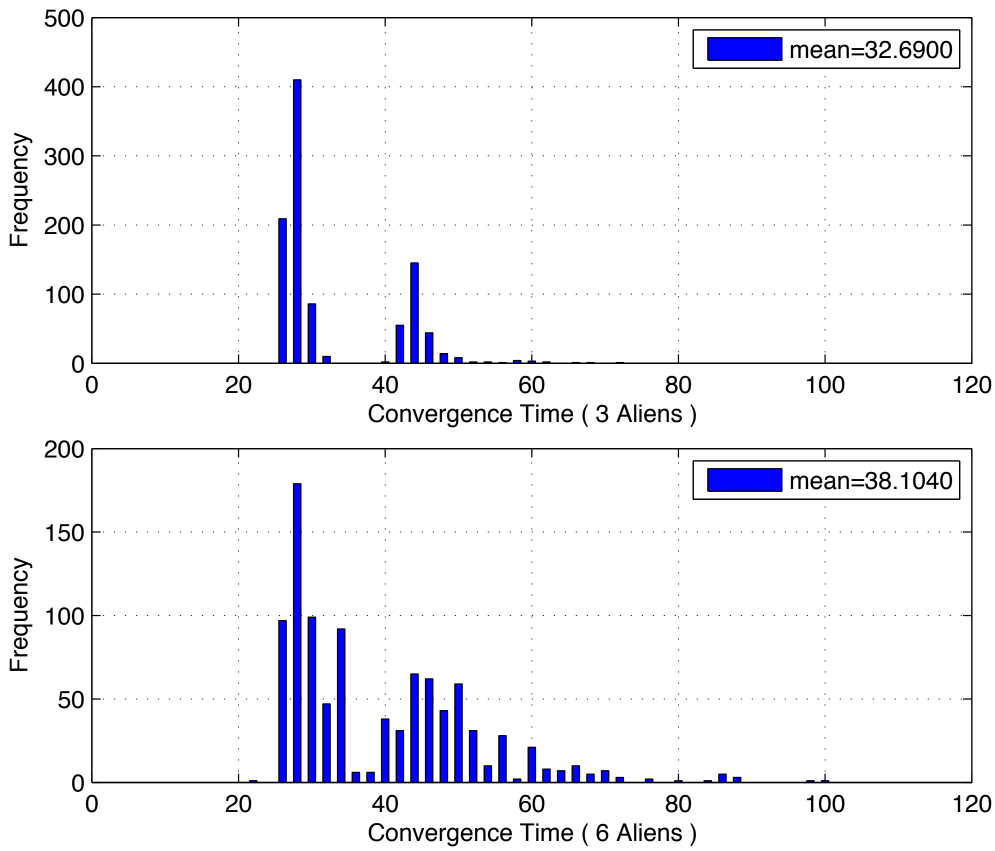

Figure 1.9: The Distribution of Convergence Time in The Game of (a) Three Aliens and (b) Six Aliens (1000 Simulation Runs)

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1.7.2 Convergence Time

To explore the idea of the convergence time in these game models, we conduct 1,000 experiments for 3-Alien games and 6-Alien games respectively. As shown in Fig. 1.9, the distribution of convergence time values is discrete. During the x_{B_i} estimation process, the numbers of Aliens' movement are within a finite discrete set. The convergence process is rapid as observed in the 1,000 experiments.

During the x_{B_i} estimation process, the number of Aliens' moves, either joining or leaving, are in a finite discrete set. Additionally, the convergence time is dominated mainly by the number of the binary search iterations, which completely depends on the distribution of Aliens' preference parameters. Each binary search iteration costs up to $\lceil \log_{(2)}(1/\xi) \rceil + 1$ stages, where $\lceil x \rceil$ is the ceiling function of x.

The maximum number of binary search is bounded by

$$min\{\lceil \log_{(exp(P_A R/h_{B_i}))}(1/\xi) \rceil, n_A + 1\}$$

which is equivalent to

$$min\{\lceil -\frac{h_{B_i} \ln \xi}{P_A R} \rceil, n_A + 1\}.$$

As mentioned before, each stage is equal to two time slots, since access point and clients play sequential game alternatively. Therefore, the maximum convergence time for our algorithm is

$$2(\lceil -log_2 \xi \rceil + 1) \cdot min\{\lceil -\frac{h_{B_i} \ln \xi}{P_A R} \rceil, n_A + 1\}. \tag{1.9}$$

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Note that the former term is a constant, and the latter is proportional to n_A, which refers to the number of joined Aliens. The number of joined Aliens n_A is bounded by the total number of Aliens in the cell, $n_{A_{total}}$. Moreover, on the basis of the observations in the 1,000 simulation runs, the convergence time is usually much smaller than the (1.9) convergence bound, which is 88 and 106 time slots in the 3-Alien and 6-Alien case respectively. In the 3-Alien simulation, the average convergence time is 32.690 time slots. The worst case is 80 slots, which occurs only once among 1,000 runs. In the 6-Alien simulation, the average convergence time is 38.104 time slots. The worst case is 106 slots, which also only occurs once among 1,000 runs. Given the same accuracy requirement ξ, the time complexity reduction from the proposed algorithm is significant compared to the brute force method. In addition, the convergence values of the bandwidth sharing ratio closely match the theoretic Nash Equilibrium results in all of these simulation runs. The average difference between the theoretic values and the converged x_{B_i} results is 5.1752×10^{-4}.

1.7.3 Ratio of Bandwidth Usage

To capture the bandwidth usage behaviors, we have conducted 1,000 experiments. Each experiment has two free roamers and seven Aliens, and all the system parameters are randomly generated. We can see the distribution of the ratio of self bandwidth usage x_{B_i} as shown in Fig. 1.10. The ratio of bandwidth to sell is $1 - x_{B_i}$. We find that Bill's strategy x_{B_i} varies significantly in those experiments, and similar results are also found in other game settings. The main reason is that the Nash equilibrium is directly related to the players' utility preference. Note that the convergence in the experimental results also match the theoretic Nash equilibrium. Both Bill's and Alien's valuation toward the bandwidth utilization make a great influence on the converged x_{B_i}. As the system param-

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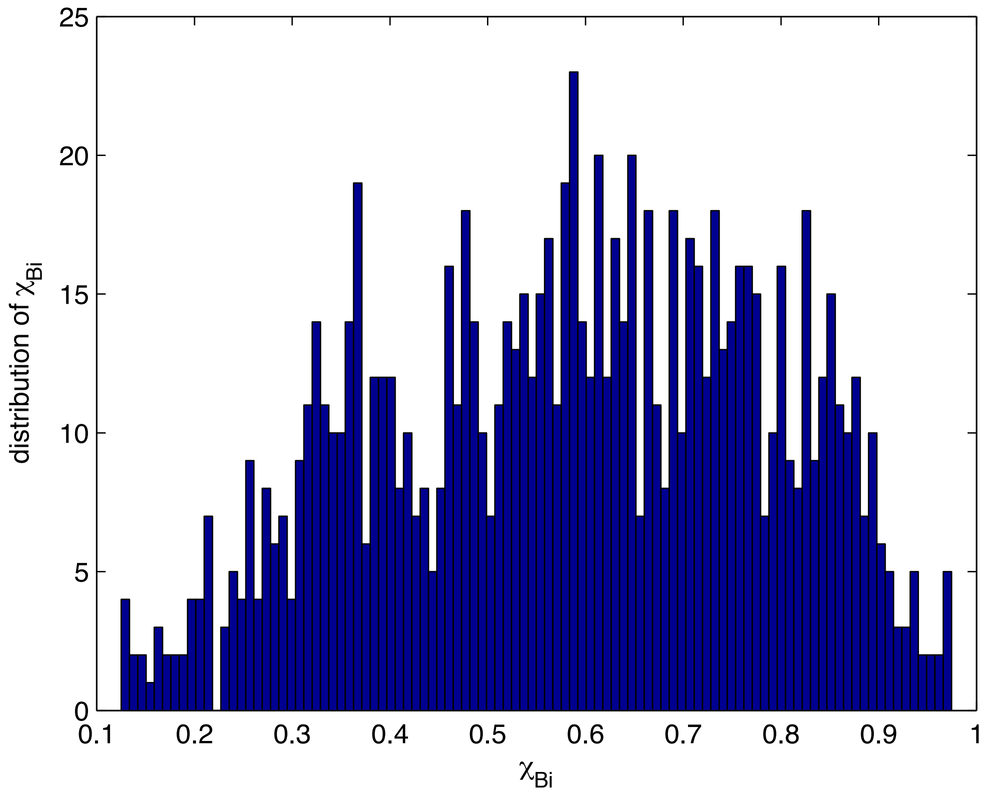

Figure 1.10: The Distribution of Bandwidth Usage Ratio x_{B_i} in 1000 Experiments (1 Bill, 2 Free Roamers, and 7 Aliens)

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eters are randomly generated, the value of x_{B_i} varies from time to time. We also observe that only a subset of relevant players, those whose utility preference parameters are within the region, might lead to the acceptance of Bill's offered bandwidth, thereby affecting the system equilibrium.

1.7.4 User Participation

The effect of the number of users and the Bill's bandwidth offering on Bill's utility are illustrated in Fig. 1.11. We simulate the system with one free roamer (i.e. one Linus or Bill as SS), four Aliens with their satisfaction coefficient, h_{A_i}, generated randomly during each experiment. Fig. 1.11(a) shows Bill's utility versus the number of joined Aliens, each little circle denotes the Nash equilibrium in one experiment.

We can see the circles gathering to about four columns, where the numbers of participants are one, two, three, and four respectively. Only one rare exception appears at $n_A = 0$ (i.e. no one uses), which is considered to be an extreme case since all the Aliens are being too picky to join the system. However, this extreme case can still occur at an extreme low odds. We can see when the number of joined Aliens goes up, so does the utility of Bill, because the effect of the payment term is much greater than the satisfaction term in Bill's utility function. The result is as expected: the more Bill shares, the more profit he gains, which is the core incentive that sustains the whole community. Also, we can see that in each of the column, the density of the circles is increasing. This implies that our system is quite efficient, in the equilibria with the same number of Aliens, the better results are more likely to be achieved (i.e. Bill is apt to achieve higher utility).

Similarly, Fig. 1.11(b) shows Bill's utility versus x_{B_i}, which also has four columns, corresponding to the columns in the left graph. We have observed that when more Aliens

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join, Bill can get more utility. Hence, we can easily distinguish these blocks, that is, from the highest to the lowest, four Aliens, three Aliens, two Aliens, and one Alien joining respectively. One exceptional circle at $x_{B_i} = 1$ is the case that no Alien uses the service and Bill keeps all his bandwidth to himself. Note that the four blocks of Nash equilibrium results are determined by the values of the four discontinuity local optimum points in Bill's utility, which is similar to the case shown in Fig. 1.1. Bill's best response is to adjust x_{B_i} to the point where the Aliens will be just in. With the prerequisite that Aliens keep joining, Bill will maximize the bandwidth for self use. Again, we can see that the proposed algorithm is efficient since it is denser when x_{B_i} is larger.

1.7.5 User Mobility

WLAN users move around in the networks. Our problem formulation and the proposed scheme could readily accommodate the user mobility issue which in the game is modeled as one player adding or exiting the game. Fig. 1.12 shows the system dynamic as an Alien first moves out of the system (at t=300) and then moves back to the system (at t=600).

Aliens may destroy the equilibrium by withdrawing from the service and joining halfway through. This simulation is meaningful since in the real world, it is an important issue for wireless mobile networks to deal with the problem that a user takes part in or moves off a service halfway when an equilibrium has already reached. We can see that there are three major pulses in our graph, each lasts comparatively very short period of time. The first, the one relatively longer than the other two, is the time to obtain the first equilibrium for the three Aliens who participate the game from the beginning. The second pulse (t=300) is the time recovering from transient state, that is, an Alien withdrawing halfway. The third pulse (t=600) is the time recovering from the condition that an Alien joins. The graph

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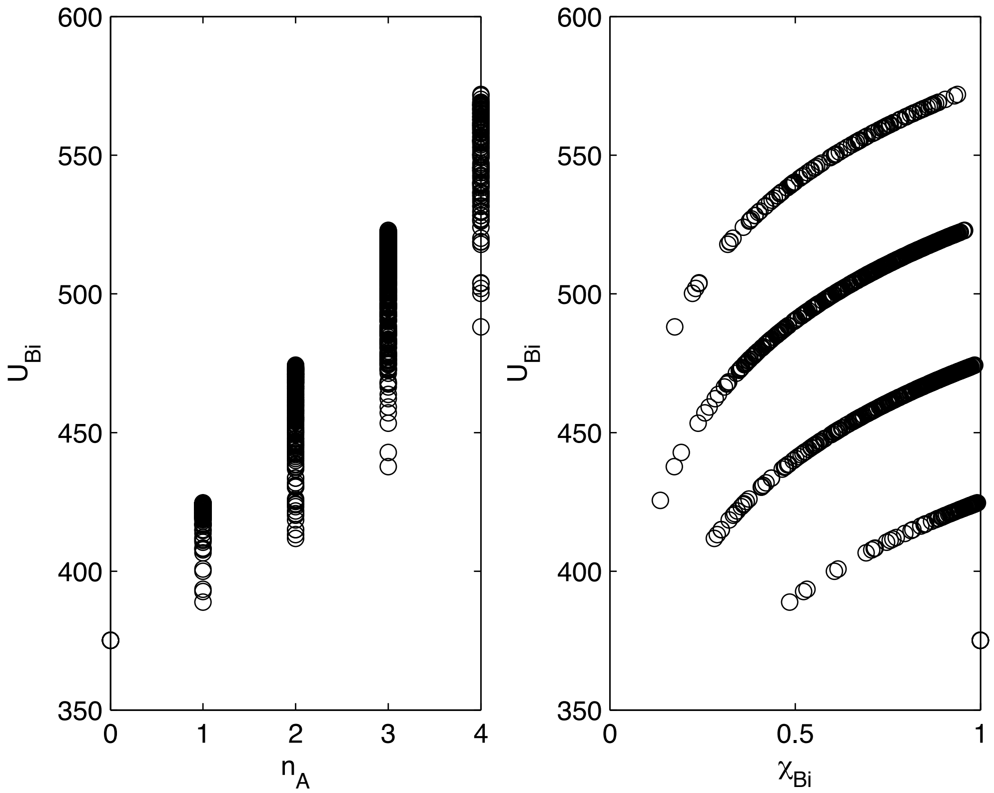

Figure 1.11: Bill's Utility versus the (a) Number of Aliens and (b) x_{B_i} (1 Bill, 1 Free Roamer and 4 Aliens)

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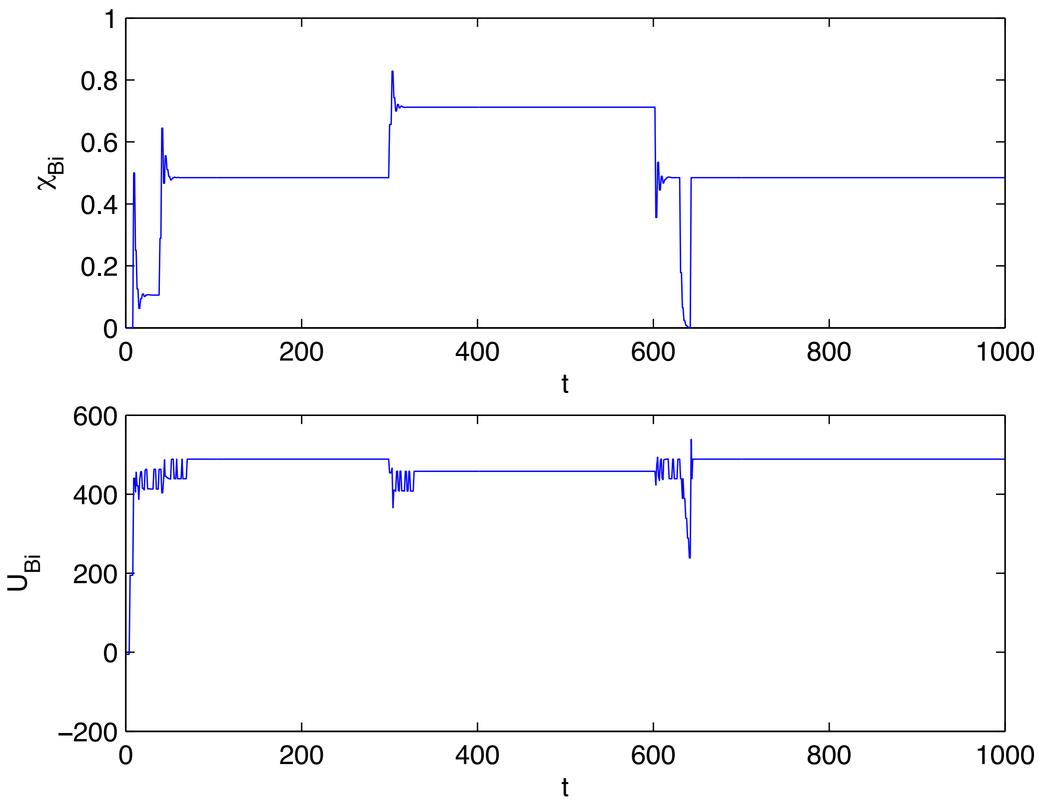

Figure 1.12: The Convergence of (a) x_{B_i} and (b) u_{B_i} when an Alien Breaks the Equilibrium by Leaving and Joining the System

also demonstrates the efficiency of our algorithm to handle leaving and joining events. Compared to the convergence time to achieve the first equilibrium, it only takes half of the time to reach the equilibrium when joining, and two third of the time when leaving. As expected, the converged x_{B_i} are identical with the first one as all the terms are the same. Also note that the traits of the lower graph are almost the same as the upper one, except for a slight time delay as the utility is the response to the previous round's strategy.

1.7.6 Variation in User Characteristics

Fig. 1.13(a) shows the relation between Bill's utility and the standard deviation of Alien's satisfaction coefficient. We can see clearly that it is trending down. The greater the dissimilarity the Aliens have, i.e. more often the extreme cases occur, the more inevitable

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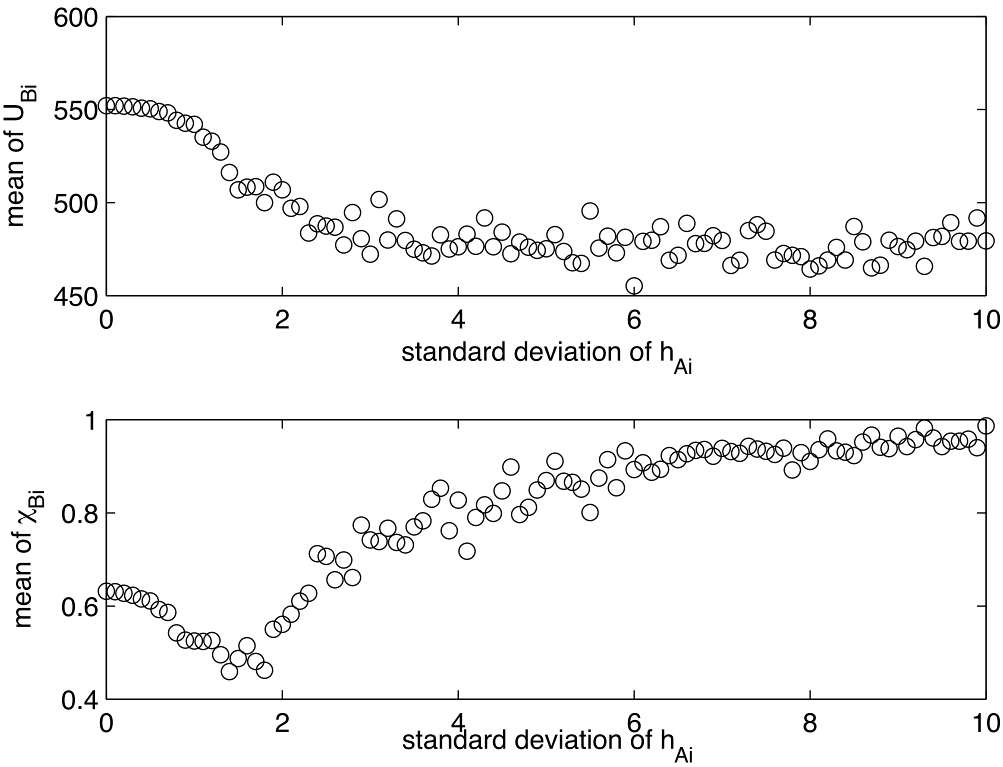

Figure 1.13: The Variation in Aliens' Characteristics h_{A_i} Affects Bill's (a) Utility and (b) Strategy

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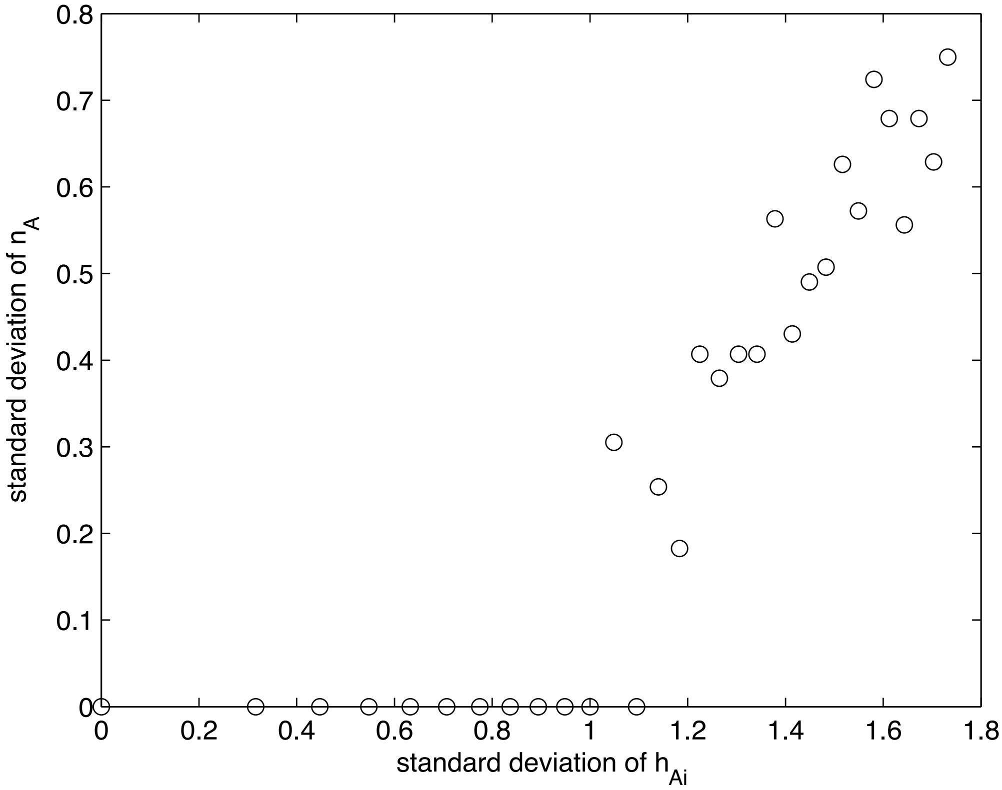

Figure 1.14: σ of n_A versus σ of h_{A_i}

for Bill to give up catering those choosy Aliens. When the dissimilarity is greater, Bill's best response is to reserve all the bandwidth for himself instead, as shown in Fig. 1.13(b). Note that Fig. 1.13(b) has a downward tendency in the beginning, which is because that when all the Aliens act similarly, it is easier for Bill to anticipate their behaviors. Thus, Bill can adopt the fairly accurate best strategy to reserve more bandwidth for self use. In Fig. 1.14, we can see that when the difference between the Aliens is greater, the more various the final Aliens number is. The reason is also same as our previous explanation; since the difference between the Aliens causes the distinctions of the bandwidth that Bill would like to share, it is intuitive that the number of Aliens will vary from the bandwidth in extreme cases. Our figure shows that when the difference between Aliens is lower than a certain value ($\sigma \approx 1$, as shown in the figure), the number of Aliens usually stays the same. When the difference is higher than the value, meaning, it enters the extreme area,

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the number of Aliens varies with h_{A_i}.

1.8 Extension to Non-logarithmic Utility

So far we have investigated the problem with the logarithm bandwidth satisfaction term in the utility function. The logarithmic utility is one of the most frequently used form in game theoretic research. Nevertheless, this study can be applied to all forms of utility functions. No matter the function is linear, convex, concave, or mixed, if the function is non-decreasing, then the proposed scheme can be applied. Since the satisfaction term represents the utility of using bandwidth, it is intuitively a non-decreasing function.

We hereby demonstrate several examples of applying logarithmic utility to different forms of utility functions. One of the examples of linear utility function is shown in Fig. 1.15(a). It is obvious since it is the combination of a linear function with positive slope (i.e. the satisfaction term) and a downward step function which reflects the behavior of the consumers (i. e. the payment term). On the other hand, Fig. 1.15(b) shows the feasibility of our decision algorithms in linear cases. The properties and the tendency of the figure in the logarithm case are observed here. The convergence is rapid and meets the theoretic result.

Now we examine a more general case based on the convex form of satisfaction, as is shown in Fig. 1.16. Similar to the previous cases, Fig. 1.16(b) shows the property of prompt convergence. Even though the difference between the convex formulation and the original logarithm formulation is remarkable (i. e. convex versus concave), the methodology we proposed is still applicable.

Eventually, after illustrating the applicability in both convex and concave cases, we give a general case example. Suppose the satisfaction function is the combination of sev-

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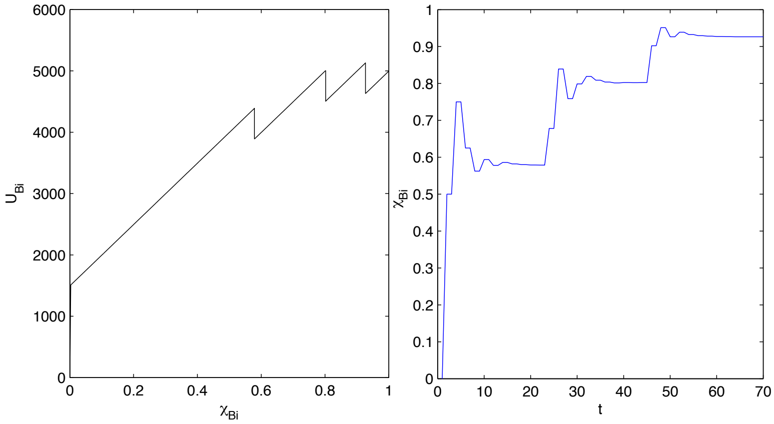

Figure 1.15: Linear Bandwidth Utility: (a) Bill's utility function (b) Convergence of the strategy

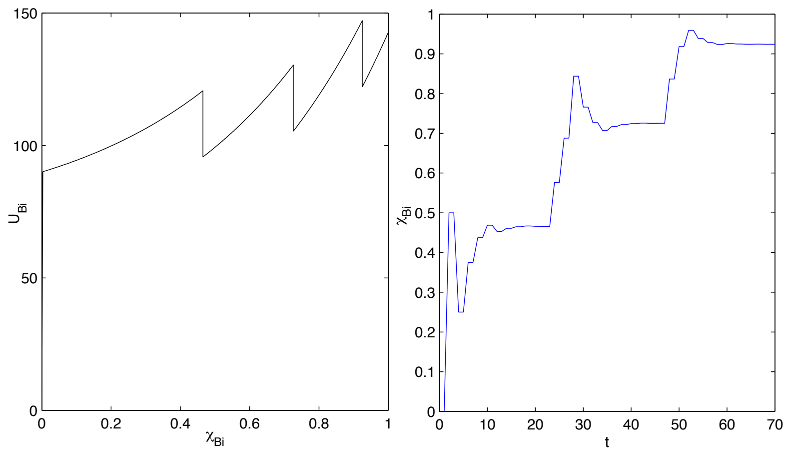

Figure 1.16: Convex Bandwidth Utility: (a) Bill's utility function (b) Convergence of the strategy

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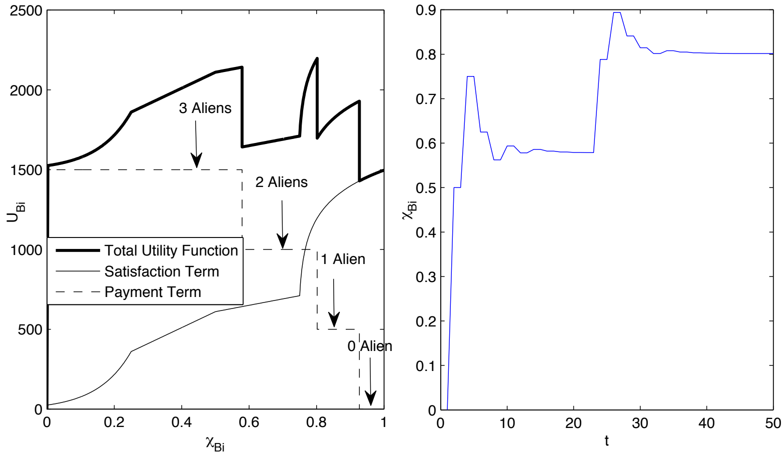

Figure 1.17: Mixed Bandwidth Utility: (a) Bill's utility function (b) Convergence of the strategy

eral segments which can be either convex or concave. As shown in Fig. 1.17(a), the dotted line is the payment term and the lower line is the bandwidth satisfaction term. The upper bold line represents the summation of the two terms, that is, the total utility function of Bill. As shown in Fig. 1.17(b), the convergence is still rapid and approximates the theoretic Nash Equilibrium value.

Finally, We would like to end this section by proving the applicability of the algorithms proposed by us. In general, if the satisfaction function is not strictly increasing, more than one Nash Equilibrium may exist. However, the following proposition still holds:

Proposition 5 *For any non-decreasing satisfaction function, there exists at least one Nash Equilibrium.*

Proof: We prove this by first justifying the existence of the best response of the access point. First, with a non-decreasing satisfaction function, the access point will derive equal or higher satisfaction if more bandwidth (or larger x_{B_i}) is used by himself. Secondly, payment made by Aliens is exactly a non-increasing function of access point's self-using bandwidth. In other words, if more bandwidth is used by the AP, then less bandwidth can

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be sold to Aliens, and thus leading to smaller or equal payment from Aliens. Therefore, given any possible profile of Aliens' join decision, the best response of AP is to decide the single variable, i.e., optimal x_{B_i} , to maximize the sum of both non-decreasing satisfaction function and non-increasing payment function. With the convex and compact domain space of x_{B_i} and single-variable finite function, a global optimal strategy must exist, so the best response of AP exists.

Moreover, given a specified x_{B_i}, Aliens has their best response as described in Corollary 1. As we know, NE is the cross-set of all players' best response. Since the best response of all players exist, the cross-set solution exists and thus NE exists.

1.9 Conclusion

In this chapter, we investigate the game theoretic model of the cooperative wireless networking service where Linus, Bill, and Alien are the three types of players in the game, and each player maximizes his own utility function. We first formulate the Bill-Alien game to model the bandwidth selling of Bill WLAN access point and the participating strategies of Alien WLAN clients. Then we formulate Linus-Alien game to model the bandwidth sharing of Linus WLAN access point and the participating strategies of Alien WLAN clients. Nash equilibria are derived in both models. The equilibria lead to the maximal utility of Bill and Linus respectively. Practical protocol implementation is also proposed for the network management. Simulation results show that the proposed implementation converges rapidly to the optimal bandwidth sharing equilibrium, which closely matches the theoretic Nash equilibria. Even though the problem formulation is based on WiFi bandwidth sharing by altruistic user and selfish users, this study might be applied to other resource sharing problems, where both altruistic and selfish users exist.

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Chapter 2

Bio-inspired Proximity Discovery and Synchronization for D2D Communications

2.1 Introduction

Device-to-device (D2D) communication is an emerging technology. This technology enables a wireless communication device to connect to another device directly. Recently, 3GPP started discussing proximity based services (ProSe)[19][20] for D2D communication in LTE. Proximity discovery is a key component for D2D communication.

Take public safety application as an example, devices are usually distributed in a broad area as shown in Fig. 2.1. Infrastructure nodes may be unavailable due to the damage from a disaster. When some devices are outside the base station's (BS) coverage, a distributed mechanism is required for devices to achieve proximity discovery and synchronization. The proximity discovery in general can be categorized into two different prob-

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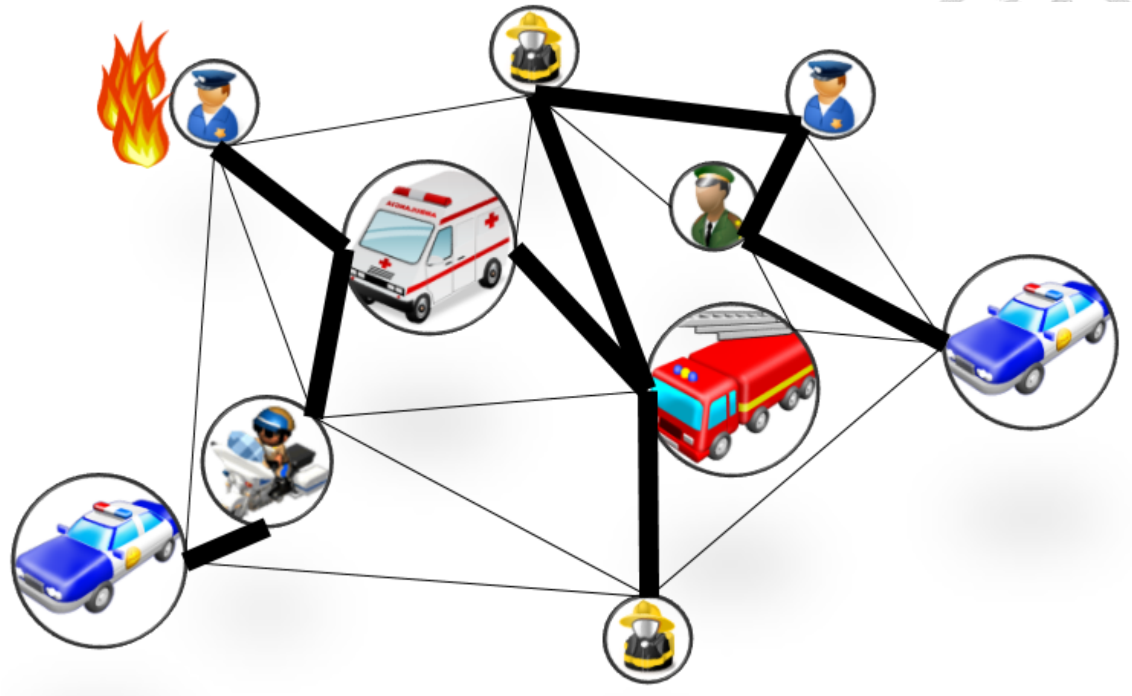

Figure 2.1: An example of a firefly spanning tree (each edge denotes a possible connection between two edges) of a D2D graph. By selecting the (heavy) edges by the proposed algorithm, the tree spanning every device makes the network synchronized.

lems, physical communication[26] and application level discovery. The integration of two proximities is desired because the signaling procedures can be reduced. For example, physical-level proximity discovery requires signal exchange among devices. Application-level proximity discovery requires the devices to find other devices with the same interests. Thus, integration of proximity discovery in view of physical communication and application is needed.

Previous works applied this sync method in different manners. Wener-Allen *et al.* implemented decentralized RFA (reachback firefly algorithm) on TinyOS-based motes, and provided theoretic improvement[22]. Tyrrell *et al.* studied an exquisite design[23] and its application[24]. Lucarelli and Wang described the general model, and the convergent condition[25]. Nevertheless, in all conventional work above, the topology (physical layer radio connectivity topology) model is always idealized.

Our LTE-A D2D simulator is constructed based on the LTE simulator [27]. It includes

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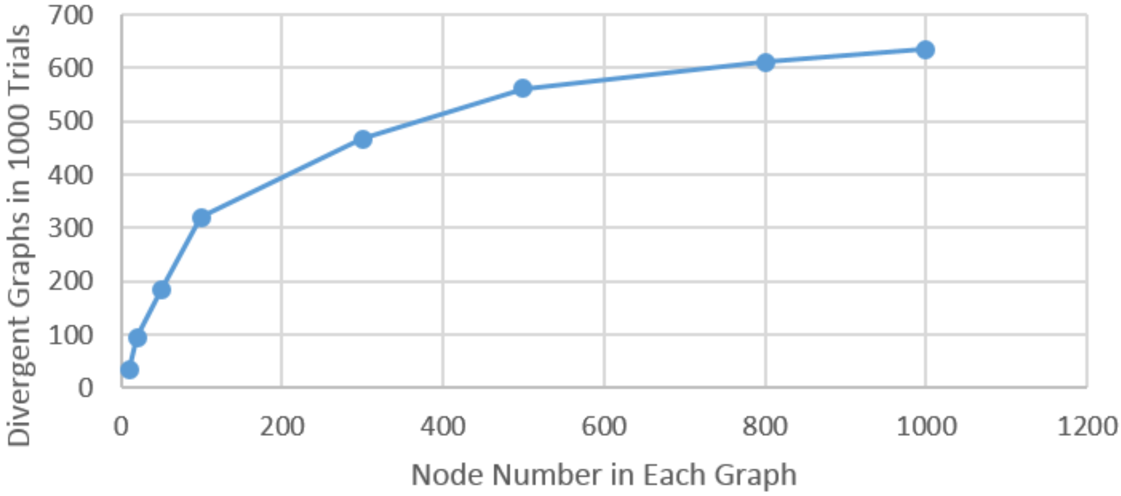

Figure 2.2: The simulation results of applying basic firefly algorithm on graphs with different scales. The test cases are randomly generated graphs with 10, 20, 50, 100, 300, 500, 800 and 1000 nodes. Each dot indicates the divergence times within 1000 trials for each test case. The detailed parameters are given in Table 2.1.

a link level simulator and a system level simulator. As observed in simulations, the network topology significantly affects the convergence. As shown in Fig. 2.2, if we naively apply the basic firefly algorithm in randomly generated topologies, a substantial ratio of systems are even unable to achieve the state sync. In current systems, like D2D communications in LTE-A, the significant growth of involved devices makes the complexity of the network marking increase. This implies that the basic firefly algorithm is no longer suitable to emerging communications. Thus, it is imperative to create a new replacement which is adaptable to all kinds of topology. In this chapter, a distributed topology-adaptive algorithm named firefly spanning tree (FST) is proposed. FST is an algorithm based on the basic firefly algorithm and a spanning tree algorithm, it is able to transform an divergent graph into a convergent graph as shown in Fig. 2.1. In simulation, the algorithm not only preserves all the benefits from the original one, additionally it outperforms other common sync methods [31] under the LTE-A D2D circumstance.

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2.2 Basic Firefly Algorithm

In the real world, synchronization between one another is one of the the largest problems that a swarm of fireflies have to face every day. This is a totally self-organized synchronization problem, resembling the one we face in communications. Surprisingly, by simply applying their innate flashes, the tough problem has an elegant solution.

Basically, the synchronous flashing progress can be modelled as the behaviour of a population of identical integrate-and-fire oscillators. It can be expressed as a phase function $\phi_i(t)$ which is integrated from zero to a certain threshold ϕ_{th}. When ϕ_{th} is reached, the oscillator flashes, or "fires." After firing, $\phi_i(t)$ is reset to zero. If not coupled with others, i.e. no firing signal is detected, the oscillator will naturally fire with a period equal to T. This may be described as $\frac{d\phi_i(t)}{dt} = \frac{\phi_{th}}{T}$.

When coupled to others, an oscillator is receptive to the firing signal of its neighbours. When a given oscillator fires, it pulls the others up by a fixed amount ϵ, or brings them to ϕ_{th}, whichever is less, i.e., $\phi_i(t) = \phi_{th} \Rightarrow \forall j \neq i : \phi_j(t^+) = min(\phi_{th}, \phi_j(t) + \epsilon)$. If the threshold ϕ_{th} is normalized to 1, when a node j fires at $t = \tau_j$, the above equation can be transformed into a piecewise linear function, $\phi_i(\tau_j) + \Delta\phi(\phi_i(\tau_j)) = min(\alpha\phi_i(\tau_j) + \beta, 1)$ with $\alpha = e^{b\epsilon}$ and $\beta = \frac{e^{b\epsilon}-1}{e^b-1}$, where $\Delta\phi$ and b denote the phase increment function and the dissipation factor, respectively.

It has already been proven that, provided that certain constraints (e.g. $\alpha > 1$, $\beta > 0$, and full meshed) on the coupling between entities are met, for an arbitrary number of entities and independent of the initial condition, the network always synchronizes. Plenty of aspects such as the effect of propagation delay, channel attenuation, and noise have also been addressed in the literature [23] [24]. Optimal selection of the parameters has also been completely discussed in some solid works. Thus, the scope of this chapter will

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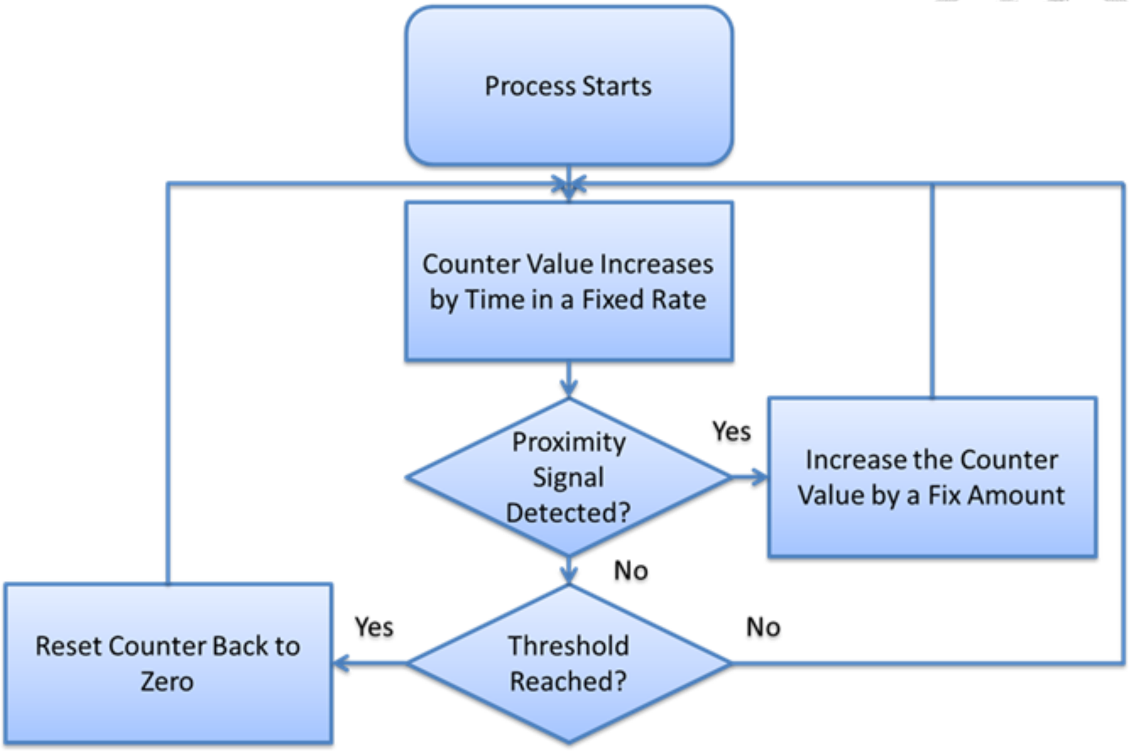

Figure 2.3: The flowchart of firefly algorithm.

not cover the above issues again.

2.3 Proximity Discovery and Synchronization

The basic concept of firefly algorithm can be applied to D2D networks as shown in Fig. 2.3. In this chapter, we proposed a distributed mechanism to achieve proximity discovery and synchronization. This mechanism enables neighbour discovery and service discovery simultaneously. In addition, it also achieves synchronization in physical communication timing and service interests in our application.

The mechanism achieves proximity discovery by sending and detecting proximity signals (PSs) among devices as shown in Fig. 2.4. Each device possesses a counter and broadcasts PSs periodically. The counter value increases by time and a threshold is set for the counter. Devices detecting the PSs will increase the counter value by a fixed rate.

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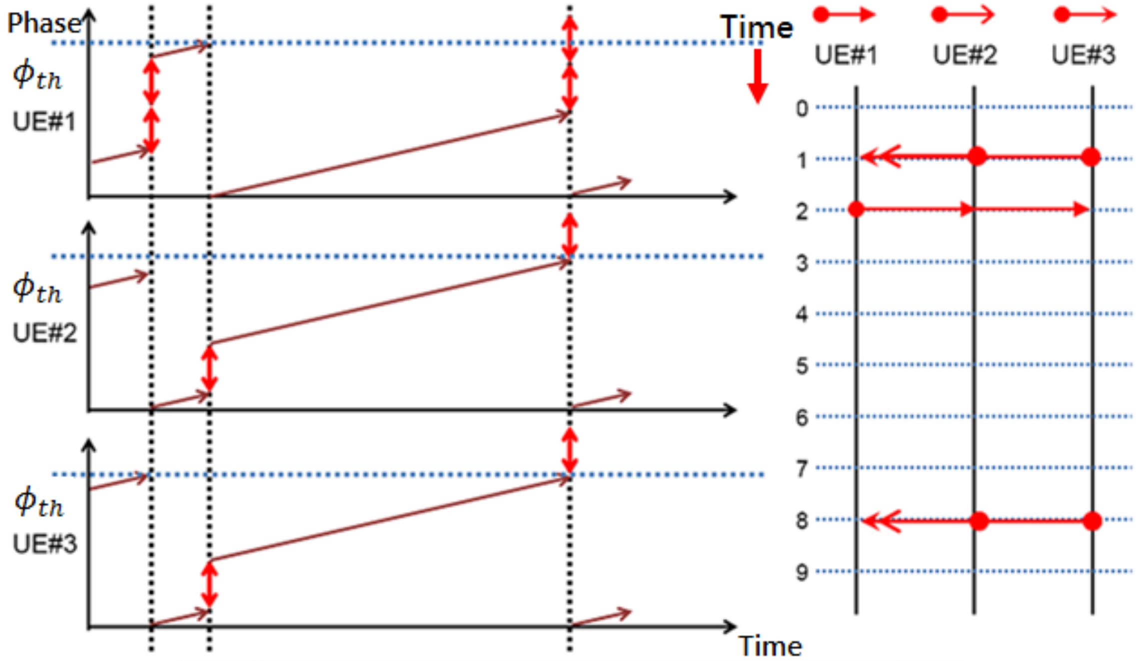

Time	0	1	2	3	4	5	6	7	8	9
UE#1	2	9	0	1	2	3	4	5	0	1
UE#2	8	0	4	5	6	7	8	9	0	1
UE#3	9	0	4	5	6	7	8	9	0	1

Figure 2.4: The signaling flow of D2D UEs' synchronization. The timing of UE#1∼UE#3 sending proximity signals (PSs) were presented in the figure. As the UE's counter exceeded the threshold, the UE will broadcast the PS, and the UEs receiving the signal will increment its counter. After several repetitions, the synchronization is finally reached once and for all.

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Once the counter reaches the threshold, the device will broadcast the PS, and then reset the counter back to the initial value like zero. The PS is broadcast to the neighbouring devices, and those devices increase their counter values accordingly. This process of PS broadcast and detection will continue until all the devices achieve synchronization in the period of signal broadcast. Note that the rate of increment and threshold may be different for different applications/services/groups.

Take LTE-A system as an example, predetermined RACH codes (or other CDMA codes) or preambles can be used to transmit the PS in the proposed scheme. Different codes indicate different application interests. This implies that a device may transmit multiple codes to indicate its interest in these multiple applications. Transmission in different radio transmission opportunity (e.g. RACH resource) can also be used to indicate different application interest.

After synchronization is reached within the group, several communication activities can be done. For example, the mechanism might be served as a keep-alive signaling method. It can also be directly applied to activate data session between devices. For instance, the PS may use two different codes (e.g. a pair RACH code). One code indicates standby and continue to the sever as the synchronization/keep-alive purpose. The other code triggers other events. We further assume that user equipments are full-duplex devices which are capable of simultaneously transmitting and receiving proximity signals. LTE-A RACH preambles are OFDM symbols, and different preambles may be transmitted in parallel without inter-group interference. However, intra-group proximity signal interference may still arise due to collision or misalignment. Such interference will influence the counter value increment. That is, devices may only detect 1 preamble while more than two devices are sending the proximity signal. Firefly algorithm still holds in this case.

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For the purpose of reducing the signaling process in both physical and application levels of proximity discovery, we introduce the concept of firefly synchronization into D2D communications. The properties of the algorithm are quite suitable to an idealized system, like a full meshed network. However, in real systems, an idealized topology is not a common case. To our best knowledge, currently there is no such research that focuses on applying similar algorithms on any randomly generated topology.

2.4 Firefly Spanning Tree

A D2D network can be formulated into a graph $G(V, E)$, where vertices V are independent devices and edges E are communication links. Links can be weighted by the strength of the PS. For preserving all the benefits of the mechanism in any randomly generated topologies, first we need to find a basic structure which is able to sustain the state of synchronization. By conducting several experiments, we found that the structure of trees may be a good candidate. In theorem 1, the stability of trees can be verified by mathematical induction.

Theorem 1 *For any acyclic graph (i.e., tree, connected graph without simple cycles), by applying the firefly algorithm, the synchronization of nodes is always achieved and sustained.*

Proof:

Mathematical induction can be used to prove that the above statement in the theorem always holds.

The basis: Show that the statement holds for the node number $n = 2$. Based on [21], when there are only two nodes (i.e. full meshed network with two nodes), the system can be synchronized. **The inductive step**: Show that if the trees with k nodes (i.e. $n = k$)

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hold, then any acyclic structures with $n = k + 1$ nodes will also hold.

A new tree T' with $k+1$ nodes can be achieved by inserting a new node L to a k-node tree T. One new connection is established between L and any of the nodes P in T. Since $\phi_P(t) = \phi_L(t), \forall P, \exists t$, the derivation can be divided into three conditions based on the impact of phase shift $\phi_P(t)$ from $\phi_{T-\{P\}}(t)$ after the insertion of L:

1. **No phase shift occurs (i.e. $\phi_P(t) = \phi_{T-\{P\}}(t)$)**: this means that the synchronizing situation of T' is equal to T. That is, the convergence is immediately completed.

2. **Phase shift occurs (i.e. $\phi_P(t) \neq \phi_{T-\{P\}}(t)$), and P reaches the threshold**: P receives a PS from $T - \{P\}$ at t_0, which means the entering of L makes P temporarily unsynchronized from $T - \{P\}$. If the PS makes P saturate (i.e. $\alpha\phi_P(t_0) + \beta \geq 1$) , L will also be lifted to saturation by P's PS since $\phi_P(t_0^-) = \phi_L(t_0^-)$. As a result, the condition of T' is equal to T.

3. **Phase shift occurs, but P does not reach the threshold**: If the PS at t_0 does not make P saturate (i.e. $\phi_P(t_0^+) = \alpha\phi_P(t_0) + \beta < 1$), P and L are temporarily unsynchronized. At the moment just before P's next saturation, say t_1, the phase of L is $\phi_L(t_1^-) = \phi_L(t_0) + (1 - (\alpha\phi_P(t_0) + \beta)) = (1 - \alpha)\phi_P(t_0) + (1 - \beta)$. After that, the PS from P is received by L, we have: $\phi_L(t_1^+) = min(1, \alpha((1 - \alpha)\phi_P(t_0) + (1 - \beta)) + \beta)$. Since $\alpha > 1$ and $\alpha\phi_P(t_0) + \beta < 1$, we have $\alpha((1 - \alpha)\phi_P(t_0) + (1 - \beta)) + \beta - 1 = (1 - \alpha)(\alpha\phi_P(t_0) + \beta - 1) > 0$, which means $\phi_L(t_1^+) = min(1, \alpha((1 - \alpha)\phi_P(t_0) + (1 - \beta)) + \beta) = 1 = \phi_P(t_1^+)$. As a result, the condition of T' is equal to T.

Since both the basis and the inductive step have been performed, by mathematical induction, the statement always holds.

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After finding a suitable structure, we still need a practical communication algorithm for transforming a network with random topology into an acyclic tree. A distributed algorithm for solving this problem is proposed. Inspired by the well-known GHS algorithm[29], we propose the **Firefly Spanning Tree (FST) Algorithm** which involves the construction of a robust spanning tree with the strongest signal strength on graphs in a fully distributed manner. It is radically different from the classical sequential problem, yet the most basic still approach resembles the well-known Boruvka's algorithm.

At the beginning of the algorithm, devices know only the weights of the links which are connected to them. After the time of linearithmic scale (i.e. the asymptotic time complexity is $O(VlogV)$), as the output of the algorithm, every device knows which of its links belong to the FST and synchronizes with the remaining neighbours. Note that the process involves two different proximity signals. PS_H is used for the synchronization between subgraphs, and PS_G is used for the regular operation of the basic firefly algorithm throughout the network. The pseudocode of FST algorithm is as described in Algorithm 1 and 2. Basically, FST is designed based on the two properties: greedy choice property and optimal substructure. By applying the two-level firefly algorithm and a greedy algorithm, we can combine all the available subgraphs into one spanning tree, i.e. the robustness of FST can be guaranteed. That is, the sum of signal strength, i.e. the weight of FST, is greater than or equal to the weight of every other spanning tree. The exact validity of FST can be mathematically proved by contradiction.

2.5 Numerical Results

In this section, system level simulations are carried out. Referring to [30] and [27], we construct a LTE-A D2D network simulator. The parameters are given in Table 2.1. As

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Algorithm 1: Firefly-Spanning-Tree(G)

for *each* $v \in G.V$ **do**
    $S_v \leftarrow$ Make-Subgraph(v);
FST $\leftarrow \{S_v | \ v \in$ G.V$\}$;
/* each $S_v \in S$ performs basic firefly algorithm (using PS_G) and the following procedures in parallel */
while $|FST| \neq 1$ **do**
    if *Head-Connect(*$S_v.Head$*,* S_v*, FST) = true* **then**
        Sync-in-Subgraph(S_v, $S_{u \neq v}$);
        /* Apply basic firefly algorithm (using PS_H) to sync the heads of S_u and S_v.*/
    else
        Change-Head(S_v);
        /* other than the current head, choose $v \in S_v$ with largest edge $\notin S_v$ as the new head of S_v */
        continue;
    Merge-Subgraph(S_v, S_u, FST);
    /* $S_v \leftarrow S_v \cup S_u$, delete S_u from S, and choose $v \in S_v$ with largest edge $\notin S_v$ as the head of S_v */
return FST;

Algorithm 2: Head-Connect(v, S_v, FST)

if v *has no adjacent vertex* $u \notin S_v$ **then**
    return false;
while *true* **do**
    /*$\{u, v\}$ is the maximum edge$\notin S_v$ adjacent to v */
    while $\phi_v \neq 1$ **do**
        if *receive PS_H from* u **then**
            send PS_H;
            if *receive PS_H from* u **then**
                return true;
            else
                return false;
    send PS_H;
    if *receive PS_H from* u **then**
        send PS_H;
        return true;
    else
        return false;

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shown in Fig. 2.5, the performance results are presented for different network sizes. Each case is evaluated in average convergence time within 1000 trials (randomly generated topologies with fixed nodes). Note that the convergence time here is the measure of how fast the devices reach the state of complete synchronization. The average convergence time is the mean of the 1000 trials. Since currently there is no other related work which is under the framework of LTE-A, the compared algorithms are chosen from other existing wireless communication systems [28]. Obviously, the centralized algorithms are invalid to our system. In addition, when we tried to implement the decentralized algorithms on our simulator, we found that most of them are either incompatible to the LTE-A system or unable to converge in random topologies. After thorough investigation, we only found the algorithm of clock-sampling mutual network synchronization (CS-MNS) [31]. As we can see in Fig. 2.5, the proposed FST outperforms CS-MNS in any size network. Also, we can observe that FST is even more efficient in larger systems due to the linearithmic time complexity.

Another performance evaluation is the exchanging messages during the converging progress. In Fig. 2.6, we can see that the trade-off of fast convergence is the number of exchanging messages. However, we can see that the deal is quite worthwhile. While FST largely outperforms CS-MNS in convergence time, the discrepancy of the two algorithms are always subtle. In fact, when in large networks (e.g. the case of 500 nodes), FST even narrowly defeated CS-MNS in terms of number of messages exchanged.

2.6 Conclusion

In this chapter, we proposed a distributed mechanism for D2D network ProSe, especially in LTE-A systems. The mechanism is able to achieve proximity discovery and synchro-

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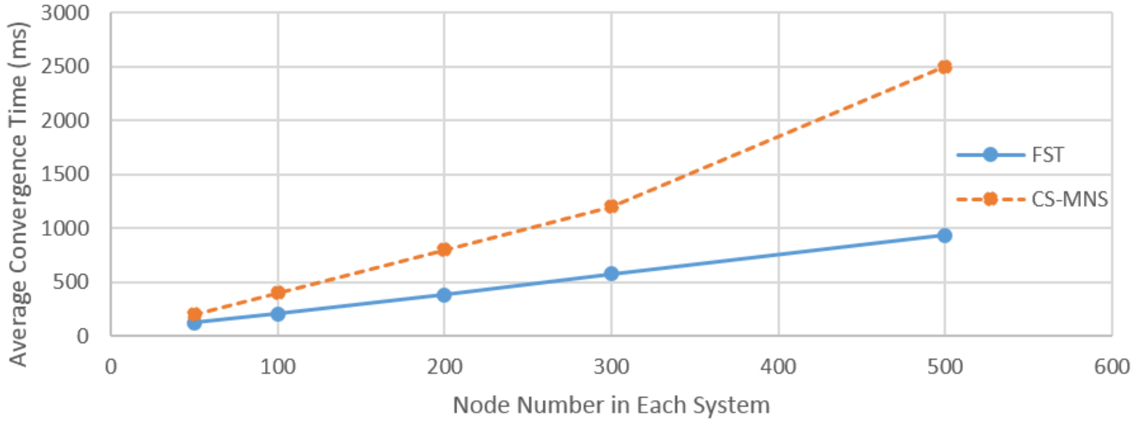

Figure 2.5: The simulation results of applying FST and CS-MNS on networks with different scales. The test cases are randomly generated networks with 100, 200, 300, 500 devices. Each dot indicates the average convergent time within 1000 trials for each test case.

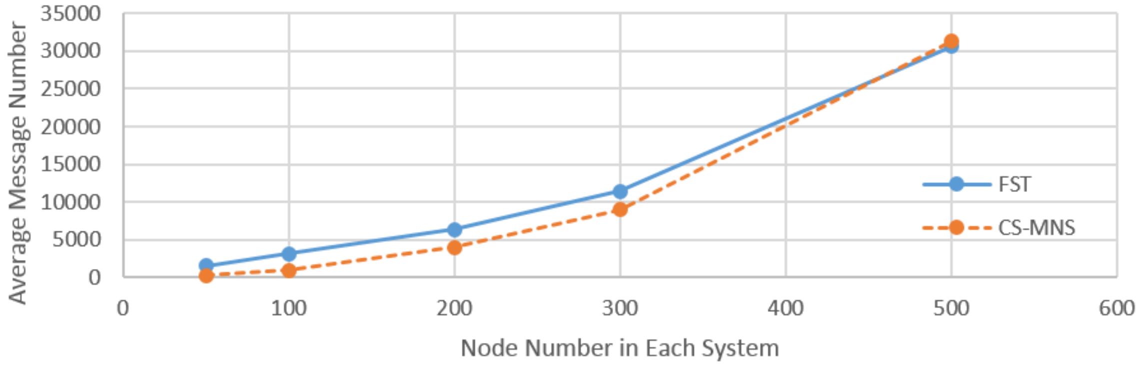

Figure 2.6: The comparison in exchanging message numbers. Each dot indicates the average number of messages exchanged during the converging procedure within 1000 trials for each test case.

Table 2.1: Simulation Parameter Values

Device Power	23 dBm (220 mW)
Threshold	-95 dBm ($3.16 * 10^{-10}$mW)
Device Density	50 devices in 100 m * 100 m areas
Propagation Model	Outdoor non-line-of-sight (dB) $P_{NLOS} = 43.5 + 25log_{10}(d)$ if $d < 60m$ $P_{NLOS} = 40.0 + 40log_{10}(d)$ otherwise
Shadowing Standard Deviation	10 dB
Time Slot	1 ms

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nization at the same time, in both physical and application level. Some essential operations can also be accomplished at the same time. In addition, a practical algorithm called FST is also given for resolving the problems caused by different topologies. Finally, the numerical results on LTE-A simulator show that the algorithm outperforms the other existing algorithms.

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