Studies on Congestion Control Using Pricing in Wireless Local Area Networks

無線 LAN における料金設定を利用した 輻轢制御に関する研究

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ABSTRACT

Along with the success of wireless local area networks (WLANs), large numbers of wireless access points (APs) are getting rapidly deployed all over the world by different businesses and homes. Especially in dense metropolitan areas, such as Tokyo, there is sufficient density of APs to achieve near-ubiquitous WLANs by sharing access amongst residents. However, most owners encrypt their networks to prevent the public from accessing them due to the increased traffic and security risk. Without a mechanism for a potential user to compensate the owner of the AP, the owner has no reason to accept the increased network traffic load and security risk that would come from allowing the public to access the network. Pricing could be used as an incentive mechanism to encourage self-interested AP owners to participate in a public wireless network.

Congestion control is of great importance when the network capacity is insufficient. Specifically, users for wireless access services, tend to localize themselves in particular areas of the network for various reasons, such as the availability of favourable network connectivity, proximity to power outlets, or geographic constraints for applying services somewhere else. Furthermore, users located in overlapping cells, tend to scan all available channels and associate themselves to the AP that has the strongest Received Signal Strength Indicator (RSSI). A key consequence of these behaviours is that the traffic load is often distributed unevenly amongst the APs, and the quality of service (QoS) cannot be guaranteed very well at heavily loaded APs.

The hot-spot congestion problem can be alleviated by: (i) balancing the load amongst multiple APs via intelligently selecting the user-AP association; and (ii) introducing connection admission control (CAC) policy for each AP. From an economic point of view, an incoming user means a potential gain to the network revenue due to the improved resource utilization. On the other hand, the incoming user may cause congestion and degradation in QoS provided for the existing users. In case that the utility decreases below the price charged, an existing user may reject the price and leave, which in turn results in a loss to the network revenue. Therefore, congestion control should play an important role in both QoS provisioning and revenue maximization.

This dissertation studies applying game theoretic techniques to modelling the pricing in conjunction with congestion control problems in WLANs. Three correlated studies with different
game theoretic formulations are presented in Chapter 3, Chapter 4 and Chapter 5, respectively.

Chapter 1 offers an introduction to the background and motivation of this dissertation. Moreover, Chapter 1 provides an overview for this dissertation.

Chapter 2 describes the related work as well as the necessary fundamentals of game theory, pricing and congestion control, forming the basis of this dissertation.

There has been a growing interest in adopting game theoretic techniques to model many communications and networking problems. In particular, game theoretic techniques have been successfully applied to the problems, such as congestion control and resource sharing in wireless networks, in which the action of one component impacts that of any other component.

Generally, there are two types of approaches to compensate the AP owners: centralized approach and decentralized approach. In the centralized approach, a third-party server is deployed to receive and process the service requests from users; while in the decentralized approach, users negotiate and pay the AP directly. There are a number of benefits in using the centralized approach. Since a third-party server maintains the system state for all APs in the network, it can monitor and control the use of the wireless bandwidth in the network. Global knowledge of the system state enables the server to easily identify heavily loaded APs and hence distribute users from a heavily loaded AP to a lightly loaded one. The decentralized approach has its advantages as well. First, as the pricing process can be done in AP locally, there is no need for the AP to carry the user’s traffic into the wired network for negotiation. This stops all unauthenticated traffic at the edge of the wired network and is thus a relatively low-risk design. Second, decentralization transfers decision-making processes to individual APs, thus reducing network management overhead and considerably increasing network scalability.

Congestion control mechanisms are used to limit the amount of traffic admitted into a particular service class so that the level of QoS of the existing users will not be degraded, while at the same time the medium resources can be efficiently utilized.

Chapter 3 proposes a "federated network" concept, in which radio resources of various WLANs are managed together. In the federated network, a third-party server involves APs deployed by different businesses, and attaches its brand name to the APs so as to ensure that a consistent QoS is offered amongst the federated APs.

The contributions of this chapter are two-fold: (i) to provide right incentives for APs that join the federated network; and (ii) to guarantee at least a minimum level of QoS to users.
The price announcements of APs are modelled as a novel second-price auction game. For each AP that accurately broadcasts her cost, it results in convergence to a Nash equilibrium solution. The proposed algorithm identifies two candidate APs (i.e., local candidate and remote candidate, if available) with the lowest price being offered for each user. The algorithm decreases the degree of blocking probability, and improves the degree of social welfare in the system in comparison to the best existing algorithms. Simulation results show that the social welfare is increased by over 40% and 10%, respectively, compared with that of fixed rate algorithm and fixed rate with roaming algorithm.

Chapter 4 takes the diversity in users’ QoS provisioning into account. Each user contends for channel access according to some user-chosen access probability. The QoS differentiation is achieved when users with high access probability transmit more often than those with low access probability. The reason why this simple MAC model is employed is because I want to abstract out the essential features of QoS-aware MAC, and hence can avoid being overwhelmed by the complexity of realistic MAC protocols.

The contribution of this chapter is to introduce and analyze an incentive-compatible load balancing approach, in which user-AP associations are intelligently determined based on not only the signal strength but also the load level at each AP.

A Stackelberg leader-follower game is structured to analyze the interaction between the federated network (leader) and users (followers). Given the best response of each user, the federated network can derive the private utility information of each user through backward induction, and determine the optimal AP-user association.

The game is composed of three steps: (i) the federated network predefines a usage-based pricing scheme; (ii) users choose their access probabilities to optimize their payoffs, namely, best response strategies; (iii) the federated network uses the best response information to determine the AP-user association, which in turn maximizes its total revenue.

In order to exploit users’ mobility for load balancing, a remote AP can also be selected by the federated network. The remote AP with better QoS (i.e., saturation throughput) encourages the users to connect. The proposed algorithm alleviates load imbalance and the consequent ineffective bandwidth utilization via intelligently selecting user-AP association within the federated network. Simulation results show that the overall revenue is increased by 8% and 5%, respectively, compared with that of network directed roaming (NDR) algorithm and distributed myopic selection (DMS).
algorithm which are presented in literatures.

Chapter 5 focuses on learning the economic behaviours of an AP and users in a decentralized model, where there is no third-party server to maintain the system state for all APs in the network. Each self-interested AP first estimates the probable utility degradation of existing users consequent upon the admission of an incoming user. Then the AP decides: (i) whether the incoming user should be accepted; and (ii) the price to be announced in order to maximize the overall revenue.

The main contribution of this chapter is to propose a distributed pricing scheme in conjunction with a CAC policy for revenue maximization in WLANs.

The interactions amongst the AP and wireless users are modelled as a multi-stage non-cooperative game. The condition, under which the proposed scheme results in a perfect Bayesian equilibrium (PBE), is investigated. In the PBE, the AP cannot increase the revenue by unilaterally deviating from the PBE strategy at any point in the game. The proposed CAC policy is completely distributed and can be implemented by individual APs using only local information. Simulation results show that the overall revenue is increased by over 50%, compared with that of fixed rate algorithm which are presented in literatures.

Finally, Chapter 6 concludes the results achieved in this dissertation and summarizes the future work.
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Chapter 1

Introduction

1.1 Background and Objectives

In recent years, IEEE 802.11 Wireless Local Access Networks (WLANs) are getting rapidly deployed all over the world by different businesses and homes. For example, in the U.S., several companies have declared their intentions to build and support nationwide WLANs, with tens of thousands of access points (APs) for providing broadband IP connectivity [1], [2]. On the other hand, a majority of city dwellers have a broadband connection and a personal AP at home. In dense metropolitan areas, there is sufficient density of APs to achieve near-ubiquitous WLANs by sharing access amongst residents. Most owners, however, encrypt their networks to prevent the public from accessing them due to the increased traffic and security risk. Without a mechanism for a potential user to compensate the owner of the AP, the AP owner has no reason to accept the increased network traffic and security risk that would come from allowing the public to access her network [3].

This study focuses on using pricing as an incentive mechanism to encourage self-interested AP owners to participate in a public wireless network. Note that a compensation mechanism itself could not eliminate the security risk. However, it is believed that monetary cost and authentication (if required) would prevent users from doing malicious acts at will. On the other hand, in order to get a return on investment, AP owners would run the risk of sharing their networks with the public.

Generally, there are two types of approaches to compensate the AP owners: centralized approach [4], [5] and decentralized approach [3], [6]. There are a number of benefits in using the
centralized approach. Since a third-party server maintains the system state for all APs in the network, it can monitor and control the use of the wireless bandwidth in the network. Global knowledge of system state enables the server to easily identify heavily loaded APs and hence distribute users from a heavily loaded AP to a lightly loaded one. The decentralized approach has its advantages as well. First, as the pricing process can be done in AP locally, there is no need for the AP to carry the user’s traffic into the wired network for negotiation. This stops all unauthenticated traffic at the edge of the wired network and is thus a relatively low-risk design. Second, decentralization transfers decision-making processes to individual APs, thus reducing network management overhead and considerably increasing network scalability [7], [8].

Deploying thousands, perhaps millions of self-interested APs is not enough for providing QoS-guaranteed services for every user. QoS provisioning is important when the network capacity is insufficient, especially for real-time streaming multimedia applications such as VoIP, online games and IP-TV. Specifically, users for wireless access services, tend to localize themselves in particular areas of the network for various reasons, such as the availability of favourable network connectivity, proximity to power outlets, or geographic constraints for applying services somewhere else. Furthermore, the users located in overlapping cells, tend to scan all available channels and associate themselves to the AP that has the strongest Received Signal Strength Indicator (RSSI) [8], [9]. A key consequence of these behaviours is that the traffic load is often distributed unevenly among the APs, and the QoS cannot be maintained very well at heavily loaded APs [10], [11].

The hot-spot congestion problem can be alleviated by: (i) balancing the load among the APs via intelligently selecting the user-AP association [12], [13]; and (ii) introducing connection admission control (CAC) mechanism for each AP [14], [15].

The proposed algorithm balances the weights of two metrics, i.e., signal strength and load, by suggesting a user to change the association from an heavily loaded AP with strong signal to a lightly loaded and cost-efficient AP, but might with weak signal. Moreover, as shown in Figure 1.1, an incoming user means a potential gain to the network revenue due to the improved resource utilization. On the other hand, the incoming user may cause congestion and degradation in QoS provided for the existing users. In case that the utility decreases below the price charged, an existing user may reject the price and leave, which in turn results in a loss of the network revenue. Therefore, CAC policy should play an important role in both QoS maintenance and revenue maximization.
1.2 Structure of the Dissertation

Overall structure of content with relations among chapters and sections is depicted in Figure 1.2. Short descriptions of each chapter are given below.

Chapter 1 offers an introduction to the background and motivation of this dissertation.

Chapter 2 describes the related work as well as the necessary fundamentals of game theory in congestion control [16], [17], forming the basis of the three correlated studies presented in Chapter 3, Chapter 4 and Chapter 5, respectively.

Chapter 3 proposes a "federated network" concept, in which a third-party server involves APs deployed by different businesses. The third-party server attaches its brand name to the APs so as to ensure that consistent QoS is offered among the federated APs. The price announcements of APs are modelled as a novel second-price auction game. For each user, the proposed algorithm identifies two candidate APs (if available) with the lowest price being offered.

Chapter 4 takes the diversity in users’ QoS provisioning into account. The proposed algorithm alleviates load imbalance and the consequent ineffective bandwidth utilization via intelligently selecting user-AP association within the federated network. A Stackelberg leader-follower game
Chapter 1: Introduction

Chapter 2: Fundamentals of Congestion Control, Pricing and Game Theory

Introduction & Fundamental

Centralized approach

Chapter 3: Auction-Based Pricing and Resource Sharing in WLANs

Diversity in users’ QoS provisioning

Chapter 4: Stackelberg-Game Modelling of Pricing and Load Distribution with QoS Differentiation in WLANs

Decentralized approach

Chapter 5: Distributed Pricing and Connection Admission Control in WLANs

No central aggregation server

Summary

Chapter 6: Conclusions and Future Work

Figure 1.2 Overall structure of content.
1.2 Structure of the Dissertation

is then formulated to obtain the optimal user-AP association.

Chapter 5 focuses on learning the economic behaviours of an AP and users in a decentralized model. The self-interested AP first estimates the possible utility degradation of existing users consequent upon the admission of an incoming user. Second, the AP decides: (i) whether the incoming user should be accepted; and (ii) the price to be announced in order to maximize the overall revenue. The condition, under which the proposed scheme results in a perfect Bayesian equilibrium (PBE) is investigated.

Finally, Chapter 6 concludes the results achieved in this dissertation and summarizes the future work.
Chapter 2

Fundamentals of Congestion Control, Pricing and Game Theory

2.1 Congestion Control and QoS Provisioning

Traffic has been growing at a faster rate than the network infrastructure, and it is widely believed that some sort of congestion control must be exercised in order to ensure the adequate use of available resources and avoid a collapse of service [18], [19].

Specifically, users for wireless access services, tend to localize themselves in particular areas of the network for various reasons, such as the availability of favourable network connectivity, proximity to power outlets, or geographic constraints for applying services somewhere else. Furthermore, users located in overlapping cells (here a cell means the coverage area of an AP), tend to scan all available channels and associate themselves to the AP that has the strongest Received Signal Strength Indicator (RSSI). A key consequence of these behaviours is that the traffic load is often distributed unevenly amongst the APs, and the QoS cannot be guaranteed very well at heavily loaded APs.

The hot-spot congestion problem can be alleviated by: (i) balancing the load amongst multiple APs via intelligently selecting the user-AP association; and (ii) introducing connection admission control (CAC) policy for each AP.
2.1.1 QoS Provisioning in IEEE 802.11 MAC Protocols

The IEEE 802.11 WLAN specifies two medium access control (MAC) mechanisms, i.e., Distributed Coordination Function (DCF) and Point Coordination Function (PCF) [20]. Guaranteeing QoS for real-time traffic is not an easy task, since the DCF is in nature contention-based and distributed. To support real-time services, the standard provides a polling-based media access in the PCF mode. However, PCF is not supported by most wireless vendors and has a poor performance [21], [22]. In addition, other problems such as hidden terminals or channel fading make things worse.

The Enhanced DCF (EDCF) [23] and other studies [24], [25] focus on using per-flow resource-based admission control combined with prioritized data transmission for real-time traffic, thus improving user’s QoS within a single cell in the network. The main drawback of these approaches is that the dynamics of the wireless network, in terms of both time of a day and location [26], are not sufficiently considered. Hence that the traffic load still tends to be distributed unevenly among the APs and the QoS cannot be maintained very well at heavily loaded APs [27], [28].

2.1.2 Channel Switching and Network Directed Roaming

As studied in [29], [30], the load imbalance problem can be alleviated by balancing the load among the APs via intelligently selecting the user-AP association. They suggest adding load information, such as packet loss rate, throughput, retransmission probability or airtime cost [15], into the beacon frames. Users could use such information in addition to the signal strength to select the APs. These approaches show nice features. However, there are two drawbacks to overcome: (i) these approaches distribute users only across available overlapping cells, hence that the load could be only locally balanced; and (ii) due to the lack of inter-operability between APs deployed by different businesses, the APs do not cooperate to balance the load across the network.

Exploiting user mobility for load distribution within an entire network is by no means a new idea. A seminal paper [31], describes a scenario where a user using her wireless connection at an airport gate cannot get enough bandwidth to complete her e-mail transmission, because many passengers at that gate are surfing the web. As a solution to this problem, a pervasive computing system helps to find a nearby gate with greater capacity and encourage the user to move to that gate.

In [4], the authors focus on distributing traffic loads within the network using a centralized ap-
2.1 Congestion Control and QoS Provisioning

A centralized server is deployed to monitor the bandwidth allocation in the entire network. The centralized server then helps to identify an AP where an incoming user’s QoS bound (i.e., a minimum and a maximum bound on the bandwidth) can be adequately met. However, due to the inherent contention-based medium access property, guaranteeing a certain amount of bandwidth to a user in WLANs is not a trivial matter in practice. Furthermore, in real networks, users are usually non-cooperative and selfish in the sense that they make decisions to maximize their individual utilities or payoffs. The network can be easily overtaken by the selfish users occupying bandwidth as much as possible.

When interactions among users are taken into account, game theory becomes a natural modelling framework [32], [33]. In [34], the authors extend the scenario described in [31] and model the system as a game in order to obtain the stable system outcomes (i.e., Nash equilibrium). However, there are two drawbacks to overcome: (i) the load at an AP is estimated based on the number of associated users. In some deployment scenarios, data flows have bursty characteristics and generate dynamic load on the APs. Therefore, the number of existing users cannot reflect the load level at each AP properly [30]; (ii) the proposed algorithm fails to produce a Nash equilibrium, when the diversity in users’ QoS maintenance is taken into account.

2.1.3 Connection Admission Control

Connection admission control (CAC) is an important component for the maintenance of QoS [35], [36]. The purpose of CAC is to limit the amount of traffic admitted into a particular service class so that the level of QoS of the existing users will not be degraded, while at the same time the medium resources can be efficiently utilized [37].

In [3], the authors investigate the economic behaviours of wireless users under an assumption that the network has unlimited capacity. They prove that fixed rate is an optimal strategy to the wireless AP, given that users have a so-called "web browsing" utility function. The "web browsing" utility grows proportionally with the time slots he gains access initially, and saturates when he no longer intends to browse. In [6], the authors think that it is only a special case that the network has unlimited capacity, or equivalently, has an adequate supply of bandwidth to meet all demands from users. So the authors generalize the model in [3] by limiting the AP to admit at most $m > 0$ users at a time, and show that the elegant results in the unlimited capacity model (charging a fixed rate at
all time) no longer apply. They propose an algorithm based on the Markovian decision theory [38] to devise the optimal pricing strategy.

However, the utility degradation of existing users, incurred by the admission of an incoming user, is not sufficiently considered in [3], [6]. Although limiting the AP to admit at most $m > 0$ users at a time [6] is more realistic, I argue that the limitation is a little bit strong. Actually, if the admission of the incoming "$m + 1"$-th user would increase her overall revenue, there is no reason to think that the AP will reject the incoming user.

2.2 Pricing

The issue of pricing must be taken into account when thinking about a complete solution to the problem of providing adequate QoS to heterogeneous users. By adopting an appropriate pricing policy and setting prices carefully, a service provider will be able to provide the necessary incentives for each user to choose the service that best matches his/her demands. Hence, over-allocation of network resources is discouraged and maximization of revenue and/or social welfare [39] can be achieved.

Over-utilization of network resources can be avoided by using pricing, which thereby can be employed as a mechanism for congestion control. Figure 2.1 shows one way to achieve this effect, namely, to dynamically set prices that reflect the current state of the network. As the network gets congested, prices increase, so users are discouraged to use the network; when the load returns to manageable levels, prices decrease, and users are encouraged to increase traffic.

The volume of traffic generated by users and the distribution of traffic over the day are influenced by time-of-day pricing and dynamic pricing policies. This ability to affect the expected load may be useful for not only managing existing resources but also dimensioning the network.

One of the debates in Internet pricing is related to whether flat rates or usage-sensitive charges should be placed on users.

2.2.1 Flat Rate

Flat rate refers to a tariff that is independent of the amount of traffic produced as well as of QoS. A flat rate is the method by which Internet access is currently charged. Since the flat rate does
Figure 2.1 Dynamically pricing that reflects the current state of the network.
not differentiate between low-load users (e.g., e-mail, Web browsing) and high-load users (e.g., multimedia applications, frequent downloading of large files). The low-load users may therefore be penalized with respect to the high-load users. Although fixed costs can be recovered, congestion costs cannot.

2.2.2 Usage-Based Pricing

Differentiated services (DiffServ) is a computer networking architecture that specifies a simple, scalable and coarse-grained mechanism for classifying and managing network traffic and providing QoS on modern IP networks. DiffServ can, for example, be used to provide low-latency to critical network traffic such as voice or streaming media while providing simple best-effort service to non-critical services such as web traffic or file transfers.

Moving from a single-service to a DiffServ architecture adds new dimensions to the pricing problem. Obviously, a flat rate does not provide enough incentives for users’ reasonable choices of services. Self-interested user may try to declare their traffic to be critical traffic and occupy the network resources as much as possible. As a consequence, the network can be easily overtaken by these self-interested users, leading to a tragedy of the commons [40]. Furthermore, the provider has no knowledge of the value of the information carried in each flow making it difficult to prioritize traffic for graceful QoS degradation at times of congestion [39].

Usage-based pricing means that prices are a function of the amount of traffic that actually flows through a connection. Usage-based pricing addresses the problems of congestion cost recovery and avoids a tragedy of the commons. However, there is anecdotal evidence that Internet users do not react favourably to usage-based pricing schemes. Certainly, such policies tend to make it more difficult for customers to budget for a network expense that is uncertain. Furthermore, additional management and billing costs to the network provider may be substantial. Finally, usage-based pricing tends to discourage the use of the Internet, a notion that many in the research and academic communities find objectionable. Most of these objections need to be addressed before usage-based pricing schemes become widely used [39].

The implementation of this type of scheme requires major structural changes not only to network management but also to users’ applications, which must be able to adapt to changes in network load quickly.
Table 2.1 Main advantages and disadvantages of each of fixed rate and usage-based pricing.

<table>
<thead>
<tr>
<th>Advantage</th>
<th>Disadvantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flat rate</td>
<td>- Easy to implement</td>
</tr>
<tr>
<td></td>
<td>- Little overhead for billing</td>
</tr>
<tr>
<td></td>
<td>- Unfair to light users</td>
</tr>
<tr>
<td></td>
<td>- No recovery of congestion costs</td>
</tr>
<tr>
<td></td>
<td>- Server overgrazing</td>
</tr>
<tr>
<td></td>
<td>- Not appropriate for differentiated QoS</td>
</tr>
<tr>
<td>Usage-based</td>
<td>- Can play a role in congestion control</td>
</tr>
<tr>
<td>pricing</td>
<td>- Increased billing complexity</td>
</tr>
<tr>
<td></td>
<td>- Increased fairness</td>
</tr>
<tr>
<td></td>
<td>- Difficult to budget for</td>
</tr>
<tr>
<td></td>
<td>- May discourage usage</td>
</tr>
</tbody>
</table>

A brief summary of the main advantages and disadvantages of each of fixed rate and usage-based pricing is presented in Table 2.1 [39].

### 2.2.3 Utility Functions

Utility functions can be used to model network users’ preferences. These functions help to describe how sensitive users are to the QoS changes. In some sense, utility can be considered as the amount of money that a user is willing to pay for certain QoS guarantees.

Ideally, utility should be described as a function of actual QoS parameters, e.g., delay or packet losses. However, in wireless access networks, it is impossible to predict such quality measures in advance, which closely depend on factors like traffic models, scheduling disciplines and network topology. Thus, the amount of a resource available to a user by the network is often used to describe the utility function instead. In this way, a user’s sensitivity to the QoS changes can still be indicated by the utility.

As described above, resources allocated to the flow or the call, which serve as an indication of expected performance, may be used to describe the utility function instead of actual predicted QoS. In this case, not only elastic but also inelastic applications need to be considered. Hard real-time applications (e.g., VoIP application controlled by SIP) that employ constant bit rate coding are
inelastic in their demand for bandwidth, due to that they require a fixed amount of bandwidth for adequate QoS, therefore, their utility can be modelled as a step function, as shown in Figure 2.2. On the other hand, traditional data applications such as e-mail are elastic, in that they incline to be tolerant of variations in delay, and can work with even minimal amounts of bandwidth. Figure 2.3 represents the utility function in this case. Soft real-time applications can be made tolerant of changes in available bandwidth by a number of ways in adaptive coding, however, some minimal amounts of bandwidth is still required. These kind of applications are partially elastic, their utility functions may take a shape as depicted in Figure 2.4 [39].
2.2 Pricing

Figure 2.3 Utility functions (elastic applications).
Figure 2.4 Utility functions (partially elastic applications).
2.3 Game-Theoretic Analysis

From an economic point of view, an incoming user means a potential gain to the network revenue due to the possible improved resource utilization. On the other hand, the incoming user may cause congestion and degradation in QoS provided for the existing users. In case that the utility decreases below the price charged, an existing user may reject the price and leave, which in turn results in a loss to the network revenue. Therefore, congestion control should play an important role in both QoS maintenance and revenue maximization.

Game theory is a mathematical tool developed to understand competitive situations in which rational decision makers interact to achieve their objectives. In recent years, there has been a growing interest in adopting game theoretic approaches to model many communications and networking problems, such as congestion control in communication networks [41], [42], cognitive radio systems [43], [44], and resource sharing in wireless/wired and peer-to-peer networks [45], [46].

2.3.1 Strategic Game and Nash Equilibrium

A strategic game is a model of interactive decision-making in which each decision-maker chooses his plan of action once and for all, and these choices of individual decision makers are made simultaneously. A game in strategic (or normal) form has three elements:

- the set of players $N$.
- the pure-strategy space $S_i$ for each player $i, i \in N$.
- and the payoff function $u_i$ that gives player $i$’s utility $u_i(s)$ for each profile $s = (s_1, ..., s_I)$ of strategies.

A Nash equilibrium is a profile of strategies such that each player’s strategy is an optimal response to the other players’ strategies [47]. The second-price auction game is specified as follows.

Example 1. A seller has one indivisible unit of object for sale. There are $I$ number of potential buyers, or bidders, with valuations $0 \leq v_1 \leq ... \leq v_I$ for the object, and these valuations are common knowledge. The bidders simultaneously submit bids $s_i \in [0, \infty)$. The highest bidder wins the object and pays the second bid (i.e., if he wins ($s_i > \max_{j \neq i} s_j$), bidder $i$ has utility $u_i = v_i - \max_{j \neq i} s_j$), and the other bidders pay nothing (and therefore have utility 0).
For each player $i$ the strategy of bidding his valuation ($s_i = v_i$) weakly dominates all other strategies. Thus, it is reasonable to predict that bidders bid their valuations in the second-price auction. Also note that because bidding one’s valuation is a dominant strategy, it does not matter whether the bidders have information about one another’s valuation. Hence, if bidders know their own valuations but do not know the other bidders’ valuations, it is still a dominant strategy for each bidder to bid his valuation.

### 2.3.2 Incomplete Information Bayesian Game

In game theory, a Bayesian game [48] is one in which information about characteristics of the other players (i.e. payoffs) is incomplete. A Bayesian game can be modelled by introducing Nature as a player in a game. Nature assigns a random variable to each player which could take values of types for each player and associating probabilities or a probability density function with those types (in the course of the game, nature randomly chooses a type for each player according to the probability distribution across each player’s type space). Modelling a Bayesian game in such a way allows games of incomplete information to become games of imperfect information (in which the history of the game is not available to all players). In a Bayesian game, the incompleteness of information means that at least one player is unsure of the type (and so the payoff function) of another player.

Such games are called Bayesian because of the probabilistic analysis inherent in the game. Players have initial beliefs about the type of each player (where a belief is a probability distribution over the possible types for a player) and can update their beliefs according to Bayes’ Rule as play takes place in the game, i.e. the belief a player holds about another player’s type might change on the basis of the actions they have played. The lack of information held by players and modelling of beliefs mean that such games are also used to analyze imperfect information scenarios.

### 2.3.3 Stackelberg Leader-Follower Game

In Economics, the Stackelberg game is used to analyze the competition in an oligopoly market. In such a market, a leader firm commits a strategy first and then other follower firms move sequential-ly. The equilibrium of the game can be obtained by backward induction. For the case of oligopoly competition in quantity, given the best response of each follower, the leader can choose the optimal
supply quantity to gain the highest profit [49].
Chapter 3

Auction-Based Pricing and Resource Sharing in WLANs

3.1 Introduction

For compensating the owners of WLANs, contractual agreements (e.g., ten dollars per month for getting wireless access at thousands of hot-spots worldwide) could be employed. This type of model has some disadvantages: (i) It is not feasible for the users who only temporarily need wireless access in one place. For instance, some users may rarely use the wireless access service in the place, or some users might have already subscribed to other contractual agreement(s) which do not cover that place. For temporary access, users might have no strong intention of subscribing to a new contractual agreement, which would require the users to pay the full charge per day or per month. (ii) It does not differentiate between short-term access and long-term access. As a consequence, the network can be easily overtaken by heavy data applications with long-term usages, leading to the tragedy of the commons phenomenon [40].

Many studies [7], [50] have focused on using pricing as an incentive mechanism to encourage the owners to share their networks with the public, where the overall payment charged grows with the time slot (e.g., 10 minutes) connected. In [51], [52], the authors study the pricing of wireless access networks with the emphasis on searching for a strategy-proof pricing mechanism. In [3], the authors investigate the economic behaviours of wireless users under a specific network topology and an assumption that the network has an unlimited capacity; in particular, they study wireless
networks using a game theoretic approach, and prove that fixed rate pricing is an optimal strategy to the AP, given that users have a so-called "web browsing" utility function. In [6], for the unlimited capacity case, the authors extend the analysis in [3] to cover the multi-hop scenario.

The previous studies constitute a theoretical foundation for the pricing of wireless networks and serve as the basis of this work. However, they do not sufficiently take into account the competition among APs deployed by different individuals and businesses. Specifically, the above-mentioned strategies (e.g., the fixed rate pricing) fail to be optimal when the AP is not the monopolist in the market.

In this work, I extend the analysis to cover the case that a user can detect several APs simultaneously, and take into account the competition among APs deployed by different individuals and businesses.

I assume that the APs in a certain area could join a federated network. As depicted in Figure 3.1, a central aggregation server (CAS) is deployed in the federated network to maintain network status by periodically collecting the load level as well as the price being offered at each AP. Each user is required to perform authentication before sending his service request. Therefore, users’ malicious acts could be well monitored and tracked.

The CAS then simplifies the selection of APs by finding two candidates with the lowest price being offered among the APs that can accommodate the user’s service request: (i) a candidate AP whose service could be provided in place (hereafter termed local candidate); and (ii) a candidate AP somewhere else whose service could be provided for the user while requiring user’s physical roaming (hereafter termed remote candidate).

I model the price announcements of APs as a game, and characterize the Nash equilibrium [47] of the system. The efficiency of the Nash equilibrium solution is evaluated via simulation studies as well. The simulation results show that the proposed algorithms perform well in a variety of user configurations.

The discussion of whether an AP would select to join the federated network or stay independently is out of the scope of this study. The goals of the proposed mechanism are: (i) to provide right incentives for APs who have joined the federated network; and (ii) to guarantee at least a minimum level of QoS to users. Hereafter, for simplicity, I assume that all the mentioned APs are associated with the federated network.
3.2 System Model

3.2.1 Federated Network

Figure 3.1 depicts IEEE 802.11 WLAN networks that comprise multiple APs deployed by different businesses. To maximize system capacity and keep the interference to a minimum, neighboring APs are configured to operate on different RF channels. Each AP has a limited transmission range and it can serve only the users that reside in the range. Furthermore, the network and the AP’s uplink here are considered to have a limited capacity. Any user’s connection request at the AP that has not enough bandwidth for allocation will not be accepted [53], [54].

At any given time a user can be associated to one AP. The user is assumed to have a quasi-static mobility pattern. In other words, the user is able to move from place to place, but he relatively tends to stay in the same physical location for long time periods. This assumption is based upon recent analysis of mobile users’ behaviours [8], [55].

A CAS is deployed in the federated network to maintain network status by periodically collecting the load level as well as the price being offered at each AP associated with that federated
network.

In the following, I first present a Per-User QoS mechanism which is proposed in [4]. To initiate QoS negotiation, each user establishes a Service Level Specification (SLS) with the network before starting his session. Each SLS specifies a minimum and a maximum bounds on the bandwidth \([b_{\text{min},k}, b_{\text{max},k}]\) that user \(k\) expects to be provided at that level. To aid the user in making a decision about his SLS, the network broadcasts service announcements in each cell advertising the remaining capacity. Providing a bandwidth range in the SLS enables the network to adaptively vary the level of QoS provided for the user as the effective capacity of each cell changes with time due to the dynamics of the wireless environment; the network attempts to guarantee user \(k\) a data rate of \(b_{\text{min},k}\) with possible provisioning up to \(b_{\text{max},k}\).

The SLS can also be used to specify other QoS parameters like delay, packet loss rate, retransmission probability and airtime cost [13], [15], but I focus the discussion on bandwidth only.

### 3.2.2 Resource Allocation

The steps involved as user \(k\) negotiates his QoS level with the network are shown in Figure 3.2. Note that the first two steps are similar to the ones in [4]:

**Step 1:** When user \(k\) arrives at the network, he discovers the existence of a service via periodically broadcasted beacons in the local network. The user’s wireless adapter associates to the AP from which it senses the strongest signal by default.

**Step 2:** After detecting the network, the user performs authentication and service level specification. To reduce the communication overhead for the user and the latency involved in getting network access, user \(k\) submits the initial service level specification, \(SLS_k\), to CAS during the session for authentication. As shown in Figure 3.3, the SLS includes: the user’s credentials required for authentication (username, password, digital certificate, etc.); the QoS bounds \([b_{\text{min},k}, b_{\text{max},k}]\); and a list of the APs (\(\text{AP\_List}_k\)), which are within communication range of the user. The latter information is obtained using the inherent ability of the user’s wireless adapter to scan the local network to locate the AP with the strongest signal. \(\text{AP\_List}_k\) contains only those APs whose signal noise ratio (SNR) is above a certain threshold, which varies depending on the user’s geographic location in the network.

The negotiation process mainly differs from the one described in [4] in the following steps:
Figure 3.2 Sequence of steps involved in QoS negotiation and admission control.
Chapter 3  Auction-Based Pricing and Resource Sharing in WLANs

Step 3: After a successful authentication verification, the CAS performs an admission test to select a local candidate (if exists) and a remote candidate (if exists) that can admit the user’s connection at the minimum capacity $b_{\min,k}$. The admission test is initially done using the lower bandwidth bound, $b_{\min,k}$. The details of candidate-AP-selection procedure are described in Section 3.3.

Step 4: The next step is to inform the user of the level of service that he has been granted through a Service Level Acknowledgement (SLAck) returned to the user. The SLAck includes two QoS tokens (for both local candidate and remote candidate). As shown in Figure 3.3, each QoS token contains: a service type field indicating if the service is provided in place or if roaming is required; the AP which provides the service; the physical (x, y) coordinates of the AP; user $k$’s network access key; and the slot price for service. The slot prices of local candidate and remote candidate are denoted by $p_0$ and $p_1$, respectively. Note that both $p_0$ and $p_1$ are determined dynamically by collecting the prices being offered by APs in the federated network. The details will also be shown in Section 3.3.

Step 5: After receiving the SLAck, the user determines either to associate to the local candidate, or to roam to the remote candidate.

A summary of the main notations used throughout Chapter 3 is given in Table 3.1.
3.3 Candidate-AP-Selection Procedure and Pricing Issues

3.3.1 Classification of APs

For ease of understanding, an example is illustrated in Figure 3.4. A user is within hearing ranges of three APs operating on different RF channels (channel a, b and c). The user’s wireless adapter associates, by default, to the AP from which it senses the strongest signal. After receiving an access service request from the user, the CAS classifies all of the APs that can meet the user’s QoS requirement in the federated network into three categories (i.e., considering SNR qualities and the locations of APs):

- **First-choice AP** (represented by a triangle filled with black color in Figure 3.4): the one whose service could be provided in place, as well as SNR is above a certain threshold;

- **Second-choice AP** (represented by a triangle drawn in solid line): the one whose service could be provided in place, but her SNR is below a certain threshold; or the one whose service is provided requiring user’s physical roaming within a certain radius $d$;

- **Invalid AP** (represented by a triangle drawn in dotted line): the one who is out of the certain radius $d$ that the user could roam.

The rationale behind the radius $d$ is to reduce the possibility of asking the user to roam a long distance for service.

3.3.2 Steps Involved in Negotiation

$N_{k}^{\text{first}}$ and $N_{k}^{\text{second}}$ are used to represent the sets of first-choice APs and second-choice APs to user $k$, respectively, and $N_{k}$ is the union of sets $N_{k}^{\text{first}}$ and $N_{k}^{\text{second}}$. Let $S = |N_{k}|$ denote the total number of APs in $N_{k}$. For $i = 1, ..., S$, let $s_{i}$ be the price offered by AP $i$.

The CAS selects the local candidate from $N_{k}^{\text{first}}$. If there are more than one first-choice AP that can meet the user’s QoS requirement, the CAS determines which one offers the lowest price. By choosing the AP with the lowest price being offered, the association control procedure tries to make the price-negotiation failure probability as low as possible, thereby maximizing the total
Figure 3.4 Classification of APs in the candidate-AP-selection procedure.
utilization in the network. Similarly, the CAS selects the remote candidate from the second-choice APs in the same way.

User $k$’ physical roaming cost is denoted by $w_k$. Note that the physical roaming cost for each user depends highly on his preference-pattern regarding the roaming. For example, some users have strict limitation on the distance of roaming, while others tend to roam longer distances for more cost-efficient services. To reduce the communication overhead for the user, the CAS performs candidate-AP-selection, estimating that the costs for physical roaming within the distance $d$ are identical for all of the users. The estimated physical roaming cost is denoted by $w_0$. Hence that the price offered by a second-choice AP will be incremented by $w_0$ to compete with a first-choice AP for providing access service for a user. $w_0$ is a constant value which could be obtained, for example, from market survey.

Let $x_i$ be a binary variable which takes value 0 when $i \in N_{k}^{\text{first}}$, and 1 when $i \in N_{k}^{\text{second}}$. Furthermore, It is assumed that AP $i^*$ offers the lowest price in $N_k$, i.e., $i^* \in N_k$ and $s_j + x_j w_0 < s_i + x_i w_0, \forall (j \in N_k$ and $j \neq i^*)$; AP $i_{\text{first}}^*$ offers the lowest price in $N_{k}^{\text{first}}$, i.e., $i_{\text{first}}^* \in N_{k}^{\text{first}}$ and $s_{i_{\text{first}}^*} < s_j, \forall (j \in N_{k}^{\text{first}}$ and $j \neq i_{\text{first}}^*)$.

The details of candidate-AP-selection procedure and pricing scheme (i.e., deciding $p_0$ and $p_1$) are described as follows.

**A. In the case that $i^* \in N_{k}^{\text{first}}$:**

AP $i^*$ is therefore selected to be the local candidate. $p_0$ is calculated as shown in Eq.(3.1).

$$p_0 = \min_{i \in N_k, i \neq i^*} (s_i + x_i w_0)$$

(3.1)

Since each AP in $N_{k}^{\text{second}}$ does not have a price advantage over AP $i^*$, no AP is selected to be the remote candidate in this case.

**B. In the case that $i^* \in N_{k}^{\text{second}}$:**

AP $i^*$ is therefore selected to be the remote candidate. $p_1$ is calculated as shown in Eq.(3.2).

$$p_1 = \min_{i \in N_k, i \neq i^*} (s_i + x_i w_0) - w_0$$

(3.2)

The selection of local candidate and calculation of $p_0$ are described as follows.

- When $|N_{k}^{\text{first}}| = 1$, the unique first-choice AP is therefore selected to be the local candidate. It is a PBE for the unique first-choice AP to pick a single maximizing value of $pP(u_k \geq p)$, say
Chapter 3 Auction-Based Pricing and Resource Sharing in WLANs

\(p^* \in \arg\max_{p} pP(u_k \geq p)\), and charge the fixed price \(p_0 = p^*\) in all time slots (please refer to [3] for the proof).

- \(u_k\) denotes user \(k\)’s utility for the item;
- \(P(u_k \geq p)\) denotes the probability that the utility is higher than the price charged.
- \(\arg\max_{p} pP(u_k \geq p)\) denotes the set of maximizers of \(pP(u_k \geq p)\).

- When \(|N_{k}^{\text{first}}| > 1\), \(p_0\) is calculated as shown in Eq.(3.3).

\[
p_0 = \min_{i \in N_{k}^{\text{first}}, i \neq i^*_{\text{first}}} s_i
\]  

(3.3)

AP \(i_{\text{first}}^*\) is therefore selected to be the local candidate.

The calculation of \(p_0\) is summarized as shown in Eq.(3.4).

\[
p_0 = \begin{cases} 
p^* & \text{if } |N_{k}^{\text{first}}| = 1, \\
\min_{i \in N_{k}^{\text{first}}, i \neq i^*_{\text{first}}} s_i & \text{if } |N_{k}^{\text{first}}| > 1,
\end{cases}
\]  

(3.4)

A user is motivated to move to a different location if and only if the price-difference gain (i.e., \(p_0 - p_1\)) justifies the physical roaming cost. In other words, there is a trade-off between the price-difference gained from changing location and the effort involved in traveling an additional distance to the AP. To select an AP, the user weighs the prices and distance parameters for the local candidate and remote candidate and then chooses the one that is optimal. The selection is therefore categorized as follows.

- **case 1**: \(i^* \in N_{k}^{\text{first}}\), and the user finally adapts himself to associating to the local candidate.
- **case 2**: \(i^* \in N_{k}^{\text{first}}\), but the user finally adapts himself to associating to the remote candidate.
- **case 3**: \(i^* \in N_{k}^{\text{second}}\), but the user finally adapts himself to associating to the local candidate.
- **case 4**: \(i^* \in N_{k}^{\text{second}}\), and the user finally adapts himself to associating to the remote candidate.
3.4 Price Announcement Game

3.4.1 Strategy Space and Payoff Function

The price announcements \((s_i, \text{for } i = 1, \ldots, S)\) of APs is modelled as a game, \(\Gamma(\text{Player, Strategy, Payoff})\), where the players of the game are the APs in the federated network, the strategy set for a AP is the set of prices, and the payoff functions are shown as follows.

In case 1, for \(i = 1, \ldots, S\), let \(c_k^i\) be AP \(i\)'s cost per slot time shared by user \(k\). The payoff function \(P_i\) for AP \(i\) is shown in Eq. (3.5).

\[
P_i = \begin{cases} 
\min_{j \neq i}(s_j + x_jw_0) - x_iw_0 - c_k^i & \text{if } s_i + x_iw_0 < \min_{j \neq i}(s_j + x_jw_0), \\
0 & \text{otherwise.}
\end{cases} 
\]

(3.5)

For simplicity, the description of the payoff functions for other cases, i.e., case 2, case 3 and case 4, is omitted. It is easy to derive the payoff functions accordingly.

The cost for AP in this work is restricted to monetary or financial cost (the cost of renewal and maintenance of network equipments, the subscription fee for wired connection, etc.). As described in the previous section, The AP's uplink is considered to have a limited capacity. Any user's connection request at the AP that has not enough bandwidth for allocation will not be accepted. This kind of limitation imposes the AP a bandwidth capacity constraint on her revenue optimization problem. Therefore, the overall cost for AP should be shared among all of the users associated to the AP.

The overall cost for AP \(i\) per slot time is denoted by \(C_{\text{slot},i}\). Moreover, let \(B_i\) be the capacity of AP \(i\), and \(U_i\) be the average bandwidth utilization of the network of AP \(i\). AP \(i\) makes a decision about \(U_i\) based upon the observation of the history of usages. The cost per slot time shared by user \(k\) is given as shown in Eq. (3.6).

\[
c_k^i = \frac{b_{\min,k}}{B_i} \times \frac{C_{\text{slot},i}}{U_i}
\]

(3.6)
3.4.2 Nash Equilibrium

In the price announcement game, APs are not interested in optimizing the social welfare. Instead, each AP selfishly tries to maximize her own revenue. This setting gives rise to a noncooperative game, and the stable outcomes of this setting are called Nash equilibrium.

**Lemma 1.** For each AP, announcing her cost truthfully for the item converges to a Nash equilibrium solution.

*Proof.* Please refer to Appendix A for the details of proof.

3.5 System Performance Evaluation

3.5.1 Evaluation Scenario

In the previous section, it is proved that with the proposed algorithm, such a system can achieve an equilibrium through theoretical analysis. Then the efficiency of the equilibrium should be evaluated sufficiently before it can be applied in the real networks.

Two classes of users are modelled, and each class has a different application profile reflecting the traffic mix generated by users of that class:

- Heavy web traffic is characterized by a 200 KB page size (including embedded graphics) and 30 sec. inter-arrival times. The QoS bounds for these users are [200 kbps, 400 kbps].

- Light web traffic has 200 KB page sizes and 1 min. inter-arrival times. The QoS bounds for these users are [100 kbps, 200 kbps].

For experimental evaluation, a model of a public-area wireless network is constructed using the Omnet simulation tool [56]. The physical and MAC layers of the wireless network are modelled according to the IEEE 802.11 standard with direct sequence spread spectrum in physical layer and distributed coordination function (DCF) in the MAC layer. These values are obtained from Omnet's default application configuration.

Furthermore, it is assumed that APs and users are randomly placed in a square area. The users arrive according to a Poisson process at rate $\lambda$ per hour and stay for a time which is exponentially
distributed with average time of 0.5 hour. The load of users’ requests is therefore set to $0.5 \times \lambda$. The traffic type of each user is randomly chosen from the two classes described previously. Other detailed simulation settings are summarized in Table 3.2.

It is assumed that the users are "rational" in the sense that they are aware of their alternatives (the two candidates), have clear preferences, and take action deliberately after some process of optimization. In particular, when $p_0 - p_1 \leq w_k$ and $u_k \geq p_0$, user $k$ associates himself to the local candidate; when $p_0 - p_1 > w_k$ and $u_k - w_k \geq p_1$, user $k$ associates himself to the remote candidate; otherwise, user $k$ determines to reject and leave.

Two other schemes are used for comparison. The first scheme is hereafter termed fixed rate scheme [7], in which the price of $AP \, i$ is randomly set to $[0\%, \, 100\%]$ above the cost $c_k^i$ shown in Eq.(3.6). Users scan all available channels and associate themselves to the AP with the lowest price being offered. The other scheme is hereafter termed fixed rate with roaming scheme. The distinction between fixed rate scheme and fixed rate with roaming scheme is that: users in fixed rate with roaming scheme can adapt themselves to roaming and associating to the AP whose service could not be provided in place. To be specific, users in fixed rate with roaming scheme could weigh the prices and distance parameters and then choose the one that is optimal.

### 3.5.2 Simulation Results

Figure 3.5 shows the blocking probability (i.e., the statistical probability that a connection cannot be established due to insufficient transmission resources in the network) as a function of arrival rate. The roaming radius $d$ here is set to 300 m. The curves show the effect of the proposed algorithm on the overall network utilization. For instance, when the arrival rate of access requests is around 90 per hour, the average blocking probability is 0.48 and 0.31 in fixed rate scheme and fixed rate with roaming scheme, respectively, and decreases to 0.29 with the proposed algorithm. This is not surprising because, with the proposed algorithm, the load can be distributed across the network and achieve greater balance and correspondingly higher overall utilization. Furthermore, the truth-telling capability of the proposed algorithm makes it easier to identify the AP with the lowest cost comparing to fixed rate with roaming scheme. Therefore, the blocking probability in terms of price-negotiation failure will be lower comparing to fixed rate with roaming scheme.

The social welfare is a microeconomic concept that represents the aggregate utility of a group
Figure 3.5 Blocking probability as a function of arrival rate.
3.5 System Performance Evaluation

Figure 3.6 Welfare of the network as a function of arrival rate.

...of individuals, such as wireless users in a wireless network. The utility of each user represents how much he values the particular level of service he is receiving. The social welfare is a basic tool to study the efficiency of resource allocation in a market. Figure 3.6 shows the social welfare as a function of arrival rate. The curves show the effect of the proposed algorithm on the social welfare. The proposed algorithm outperforms the other two counterparts, especially makes a large gain compared with the fixed rate scheme.

For price-based roaming, the cost for users depends upon the distance that they have to travel for reaching an AP that can accommodate their service requests. To explore the tradeoff between roaming distance and the effectiveness of price-based roaming, I simulate a network where the radius within which users could roam is progressively increased. The arrival rate here is set to 90 per hour. The results, plotted in Figure 3.7 and Figure 3.8, show a performance gain with roaming radius, which begins to level off at 100m, in both blocking probability and social welfare.
However, the benefit of this increase comes at the physical roaming cost to reach the new cell.

### 3.6 Concluding Remarks

This study focuses on learning the economic behaviours of the APs within a CAS-based federated network, and using a game theoretic approach to analyze the interactions among them. It has been proved that, for each AP that accurately broadcasts her cost of access, it results in convergence to a Nash Equilibrium solution. The efficiency of the Nash equilibrium solution is evaluated via simulations. The algorithm decreases the degree of blocking probability in the system, and improves the degree of social welfare in the system in comparison to the existing fixed rate and the fixed rate with roaming schemes.
Figure 3.8 Welfare of the network as a function of roaming radius.
Table 3.1 Summary of the main notations.

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SLS&lt;sub&gt;k&lt;/sub&gt;</td>
<td>Initial service level specification of user k</td>
</tr>
<tr>
<td>&lt;i&gt;b&lt;/i&gt;&lt;sub&gt;min,k&lt;/sub&gt;</td>
<td>Minimum bound on the bandwidth of user k</td>
</tr>
<tr>
<td>&lt;i&gt;b&lt;/i&gt;&lt;sub&gt;max,k&lt;/sub&gt;</td>
<td>Maximum bound on the bandwidth of user k</td>
</tr>
<tr>
<td>AP_List&lt;sub&gt;k&lt;/sub&gt;</td>
<td>List of the APs which are within communication range of user k</td>
</tr>
<tr>
<td>&lt;i&gt;p&lt;/i&gt;&lt;sub&gt;0&lt;/sub&gt;</td>
<td>Slot price of local candidate</td>
</tr>
<tr>
<td>&lt;i&gt;p&lt;/i&gt;&lt;sub&gt;1&lt;/sub&gt;</td>
<td>Slot price of remote candidate</td>
</tr>
<tr>
<td>&lt;i&gt;N&lt;/i&gt;&lt;sub&gt;first&lt;/sub&gt;&lt;sup&gt;k&lt;/sup&gt;</td>
<td>Set of first-choice APs to user k</td>
</tr>
<tr>
<td>&lt;i&gt;N&lt;/i&gt;&lt;sub&gt;second&lt;/sub&gt;&lt;sup&gt;k&lt;/sup&gt;</td>
<td>Set of second-choice APs to user k</td>
</tr>
<tr>
<td>&lt;i&gt;N&lt;/i&gt;&lt;sub&gt;k&lt;/sub&gt;</td>
<td>Union of sets &lt;i&gt;N&lt;/i&gt;&lt;sub&gt;first&lt;/sub&gt;&lt;sup&gt;k&lt;/sup&gt; and &lt;i&gt;N&lt;/i&gt;&lt;sub&gt;second&lt;/sub&gt;&lt;sup&gt;k&lt;/sup&gt;</td>
</tr>
<tr>
<td>&lt;i&gt;S&lt;/i&gt;</td>
<td>Total number of APs in &lt;i&gt;N&lt;/i&gt;&lt;sub&gt;k&lt;/sub&gt;</td>
</tr>
<tr>
<td>&lt;i&gt;w&lt;/i&gt;&lt;sub&gt;k&lt;/sub&gt;</td>
<td>User k’s physical roaming cost</td>
</tr>
<tr>
<td>&lt;i&gt;w&lt;/i&gt;&lt;sub&gt;0&lt;/sub&gt;</td>
<td>Estimated physical roaming cost</td>
</tr>
<tr>
<td>&lt;i&gt;u&lt;/i&gt;&lt;sub&gt;k&lt;/sub&gt;</td>
<td>User k’s utility for access service</td>
</tr>
<tr>
<td>&lt;i&gt;d&lt;/i&gt;</td>
<td>Maximum roaming distance</td>
</tr>
<tr>
<td>&lt;i&gt;x&lt;/i&gt;&lt;sub&gt;&lt;i&gt;i&lt;/i&gt;&lt;/sub&gt;</td>
<td>Binary variable which takes value 0 when &lt;i&gt;i&lt;/i&gt; ∈ &lt;i&gt;N&lt;/i&gt;&lt;sub&gt;first&lt;/sub&gt;&lt;sup&gt;k&lt;/sup&gt;, and 1 when &lt;i&gt;i&lt;/i&gt; ∈ &lt;i&gt;N&lt;/i&gt;&lt;sub&gt;second&lt;/sub&gt;&lt;sup&gt;k&lt;/sup&gt;</td>
</tr>
<tr>
<td>&lt;i&gt;i&lt;/i&gt;&lt;sup&gt;*&lt;/sup&gt;</td>
<td>Index of AP who offers the lowest price in &lt;i&gt;N&lt;/i&gt;&lt;sub&gt;k&lt;/sub&gt;</td>
</tr>
<tr>
<td>&lt;i&gt;i&lt;/i&gt;&lt;sub&gt;first&lt;/sub&gt;&lt;sup&gt;*&lt;/sup&gt;</td>
<td>Index of AP who offers the lowest price in &lt;i&gt;N&lt;/i&gt;&lt;sub&gt;first&lt;/sub&gt;&lt;sup&gt;k&lt;/sup&gt;</td>
</tr>
<tr>
<td>&lt;i&gt;s&lt;/i&gt;&lt;sub&gt;&lt;i&gt;i&lt;/i&gt;&lt;/sub&gt;</td>
<td>Price offered by AP &lt;i&gt;i&lt;/i&gt; for access service</td>
</tr>
<tr>
<td>&lt;i&gt;c&lt;/i&gt;&lt;sub&gt;&lt;i&gt;k&lt;/i&gt;&lt;/sub&gt;&lt;sup&gt;i&lt;/sup&gt;</td>
<td>Cost per slot time of AP &lt;i&gt;i&lt;/i&gt; shared by user &lt;i&gt;k&lt;/i&gt;</td>
</tr>
<tr>
<td>&lt;i&gt;P&lt;/i&gt;&lt;sub&gt;&lt;i&gt;i&lt;/i&gt;&lt;/sub&gt;</td>
<td>Payoff function of AP &lt;i&gt;i&lt;/i&gt;</td>
</tr>
<tr>
<td>&lt;i&gt;λ&lt;/i&gt;</td>
<td>Arrival rate of users’ requests</td>
</tr>
<tr>
<td>&lt;i&gt;C&lt;/i&gt;&lt;sub&gt;slot,i&lt;/sub&gt;</td>
<td>Overall cost per slot time of AP &lt;i&gt;i&lt;/i&gt;</td>
</tr>
<tr>
<td>&lt;i&gt;B&lt;/i&gt;&lt;sub&gt;&lt;i&gt;i&lt;/i&gt;&lt;/sub&gt;</td>
<td>Capacity of AP &lt;i&gt;i&lt;/i&gt;</td>
</tr>
<tr>
<td>&lt;i&gt;U&lt;/i&gt;&lt;sub&gt;&lt;i&gt;i&lt;/i&gt;&lt;/sub&gt;</td>
<td>Average bandwidth utilization of AP &lt;i&gt;i&lt;/i&gt;</td>
</tr>
</tbody>
</table>
Table 3.2 Summary of the simulation settings.

<table>
<thead>
<tr>
<th>Description</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size of the square area</td>
<td>$300 \times 300 \text{ m}^2$</td>
</tr>
<tr>
<td>Number of APs</td>
<td>6</td>
</tr>
<tr>
<td>Raw data rate at which each AP operates</td>
<td>11 Mbps</td>
</tr>
<tr>
<td>Power level at which each AP operates</td>
<td>100 mW</td>
</tr>
<tr>
<td>Transmission range of each AP</td>
<td>100 m</td>
</tr>
<tr>
<td>Threshold value of SNR</td>
<td>4 dB</td>
</tr>
<tr>
<td>Range in which $c_k^j$ is uniformly distributed</td>
<td>[10, 20]</td>
</tr>
<tr>
<td>Range in which $u_k$ is uniformly distributed</td>
<td>[0, 100]</td>
</tr>
<tr>
<td>Range in which $w_k$ is uniformly distributed</td>
<td>[0, 10]</td>
</tr>
<tr>
<td>Estimated physical roaming cost ($w_0$)</td>
<td>5</td>
</tr>
</tbody>
</table>
Chapter 4

Stackelberg-Game Modelling of Pricing and Load Distribution with QoS Differentiation in WLANs

4.1 Introduction

In dense metropolitan areas, it is often the case that a user can detect several APs simultaneously. Users located in overlapping cells, however, tend to scan all available channels and associate themselves to the AP that has the strongest Received Signal Strength Indicator (RSSI). A key consequence of this behaviour is that the traffic load is often distributed unevenly among the APs [10], [11].

To address this problem, I introduce and analyze an incentive-compatible load balancing approach, in which user-AP associations are intelligently determined based on not only the signal strength but also the load level at each AP.

In particular, it is assumed that APs deployed by different providers (e.g., small businesses and individuals) are able to select to join into a federated network, such as [1], [2]. A Central Aggregation Server (CAS), which is independent from each provider’s financial interests, is deployed into the federated network to keep track of the load level at each AP [57].

The CAS attaches its brand name to the APs and ensures that a consistent product is offered among the APs deployed by different providers. The CAS also handles the billing for the ser-
After receiving the service request from each user, the CAS helps to find an AP that can best accommodate the service request. Generally, the mission of CAS is to select an AP for each user from two kinds of candidate APs (if exist): (i) a candidate whose service could be provided in place (hereafter termed \textit{local candidate}); and (ii) a candidate whose service could be provided for the user while requiring user’s physical roaming (hereafter termed \textit{remote candidate}).

As depicted in Figure 4.1, the algorithm trades off signal strength with load by suggesting a user to change the association from a heavily loaded AP with stronger signal (i) to a lightly loaded local candidate with possibly weaker signal; or (ii) to a lightly loaded remote candidate whose service is provided requiring user’s physical roaming.

This study focuses on learning the economic behaviours of the wireless users, and structuring a Stackelberg leader-follower game [47] to obtain the optimal user-AP association.
4.2 System Model

4.2.1 QoS Differentiation

The model I am envisioning assumes that each user communicates with a single AP directly. In order to maximize the system capacity and keep the interference to a minimum, neighboring APs (if exist) are configured to operate on different RF channels. A CAS is deployed in the federated network to maintain network status by periodically collecting the load level at each AP.

Moreover, it is assumed that users always have packets available for transmission. Namely, the network is operated in saturation conditions [58]. Each user contends for channel access according to some user-chosen access probability. A transmission is successful if and only if there is a single transmission attempt. Hence that QoS differentiation is achieved when users with high access probability transmit more often than those with low access probability [59].

The reason why this simple MAC model is employed is because I want to abstract out the essential features of QoS-aware MAC, so as to avoid being overwhelmed by the complexity of realistic MAC protocols. For window-based protocols such as IEEE 802.11, there is a direct correspondence between access probability and window size [60]. Therefore, the analysis and related results here can be extended to such scenarios easily.

4.2.2 Saturation Throughput

Let $u = \{\xi_1, \xi_2, ..., \xi_N\}$ be the vector of access probabilities for the user 1, 2, ...N. The saturation throughput [60] of user $k$ is given by $\tau_k$ as follows.

$$\tau_k = \xi_k \prod_{j=1,j\neq k}^{N} (1 - \xi_j) \quad (4.1)$$

User demand is assumed to be elastic [61], and the utility is given by $U_k(\tau_k)$ as follows.

$$U_k(\tau_k) = \alpha + \theta_k \ln(\tau_k) \quad (4.2)$$

where $\theta_k$ is a user-dependent scale factor and can be thought of as a parameter representing the priority of user $k$’s willingness to pay. $\alpha$ is a constant.
As stated in Section 3.1, in most cases, commercial wireless service providers offer users fixed-price plans (e.g., ten dollars per month for getting wireless access at three million hot-spots worldwide). The fixed-price plans do not differentiate between short-term access and long-term access. As a consequence, the network can be easily overtaken by heavy data applications with long-term usages, leading to the tragedy of the commons phenomenon [40]. Due to the possible congestion, for example, AT&T stopped offering the fixed-price plan to its new smart-phone customers in 2010.

A usage-based pricing is hence employed. The CAS proposes a price for access, which is set to be a linear function of the user-chosen access probability. The user can either accept the price and connect, or reject and leave. The service session ends at the first time the user rejects the CAS’s proposal, including three cases: (i) the incoming user finds the slot price is too high to accept; (ii) the existing user’s utility decreases below the price charged due to congestion; and (iii) the existing user does not intend to connect any more. The overall payment charged grows proportionally with the time each user connects.

### 4.3 QoS Negotiation and Admission Control

#### 4.3.1 Classification of APs

The CAS maintains all per-cell state for the entire network, it can monitor and control the use of the wireless bandwidth efficiently. Knowledge of the system state enables the CAS to easily identify heavily loaded APs and hence distribute traffic loads from a heavily loaded AP to a lightly loaded AP.

Here, the same example as that shown in Section 3.3.1 is used. A user is within hearing ranges of three APs operating on different RF channels (channel a, b and c), as illustrated in Figure 3.4. The user’s wireless adapter associates, by default, to the AP from which it senses the strongest signal temporarily.

After receiving a service request from the user, the CAS classifies all of the APs in the federated network into three categories according to SNR (Signal Noise Ratio) and the locations of APs:

- **First-choice AP**: the one whose transmission range can cover the user, as well as SNR is above a certain threshold;
Second-choice AP: the one whose transmission range can cover the user, but SNR is below a certain threshold; or the one whose service is provided requiring user’s physical roaming within a certain distance $d$;

Invalid AP: the one who is out of the certain distance $d$ that the user could roam.

The rationale behind the maximum roaming distance $d$ is to reduce the possibility of asking the user to roam a long distance for service.

### 4.3.2 Steps Involved in Negotiation

The steps involved in QoS negotiation and admission control [4] are shown in Figure 4.2.
Chapter 4  Stackelberg-Game Modelling of Pricing and Load Distribution with QoS
Differentiation in WLANs

Step 1: User $k$ arrives at the federated network, and detects the existence of APs via beacons periodically broadcasted in the federated network. In order to reduce network management overhead, pricing information is also contained in the beacons.

Step 2: The user performs authentication and indicates his own value of access probability, through sending a Service Level Specification (SLS) packet [4]. As shown in Figure 4.3, the SLS packet contains: username, password, access probability, and a list of APs (i.e., $AP_{List_k}$), which includes the APs that are within communication range of the user.

Step 3: The CAS selects a candidate AP (if exists) that can best accommodate the user’s service request. The details of candidate-AP-selection procedure are described later in Section 4.4.

Step 4: The CAS informs the user of the candidate AP through sending a Service Level Acknowledgement (SLAck) packet. As shown in Figure 4.3, the SLAck packet contains: a service type field indicating if the service is provided in place or if roaming is required; the AP which provides the service; the physical coordinates of the AP; user $k$’s network access key; and the estimated saturation throughput.

Step 5: The user determines either to associate to the candidate AP, or to reject and leave.

Note that the negotiation process mainly differs from the one described in [4] as well as Chapter 3 in the following aspects:
4.4 Stackelberg Game and Revenue Maximization

4.4.1 Oligopoly Market and Stackelberg Game

In Economics, the Stackelberg game is used to analyze the competition in an oligopoly market. In such a market, a leader firm commits a strategy first and then other follower firms move sequentially. The equilibrium of the game can be obtained by backward induction. For the case of oligopoly competition in quantity, given the best response of each follower, the leader can choose the optimal supply quantity to gain the highest profit [49].

This Stackelberg game structure is applied to obtain the equilibrium of bandwidth sharing between the CAS and the wireless users, under an assumption that the CAS and the wireless users are rational in the sense that they are aware of their alternatives, have clear preferences, and take action deliberately after some process to maximize their profits. The game, \( \Gamma(\text{Player}, \text{Strategy}, \text{Payoff}) \), is described as follows:

- **Player**: The CAS and the wireless users are the players of this game.
- **Strategy**: For a wireless user, the strategy is the selection of access probability; and for the CAS, the strategy is the selection of user-AP association.
- **Payoff**: For both the CAS and the wireless users, the payoffs are the corresponding profits.

4.4.2 Best Response

Let \( N_l \) represent the number of existing users in the cell of AP \( l \). The access probabilities chosen by the existing users of AP \( l \) and the incoming user \( N_l + 1 \), are denoted by \( \xi_j^{(l)} \), \( \forall j \in \{1, 2, \ldots, N_l\} \)
Chapter 4 Stackelberg-Game Modelling of Pricing and Load Distribution with QoS

4.4.3 Backward Induction

Based on the best response of each user (i.e., $\xi^{(l)}_{N_l+1} = \xi^{(l)}_{N_l+1} = \theta_{N_l+1} / \beta$ and $\xi^{(l)}_j = \xi^{(l)}_j = \theta_j / \beta, \forall j \in \{1, 2, ..., N_l\}$), the CAS can induce the $\theta$-value of each user as follows:

$$\theta_{N_l+1} = \beta \xi^{(l)}_{N_l+1}$$  (4.5)

$$\theta_j = \beta \xi^{(l)}_j, \forall j \in \{1, 2, ..., N_l\}$$  (4.6)

The utility of each existing user decreases with the admission of new users. In case that the utility decreases below the price charged, the existing user may reject the price and leave. This imposes the CAS a capacity constraint on its payoff maximization problem. Intuitively, the CAS should associate the incoming user to a lightly loaded AP in order to achieve the highest payoff.

4.4.4 Subgame Perfect Nash Equilibrium

The payoff of the CAS is obtained from the net revenue gained from existing users and the incoming user. When the incoming user is associated to AP $l$, the payoff of the CAS can be defined by

$$\phi_{N_l+1} (\xi^{(l)}_{N_l+1}) = \alpha + \theta_{N_l+1} \ln \left[ \frac{\xi^{(l)}_{N_l+1}}{\prod_{j=1}^{N_l} (1 - \xi^{(l)}_j)} \right] - \beta \xi^{(l)}_{N_l+1}$$  (4.3)

Therefore, the optimal access probability can be obtained by differentiating the profit function and then setting it to zero. The unique optimal solution is given by

$$\xi^{(l)}_{N_l+1} = \theta_{N_l+1} / \beta$$  (4.4)

and $\xi^{(l)}_{N_l+1}$, respectively. Furthermore, the prices charged are set to be $\beta \xi^{(l)}_j, \forall j \in \{1, 2, ..., N_l+1\}$.
4.4 Stackelberg Game and Revenue Maximization

\[ \psi(l) = \arg \max_{l \in L} \left[ \beta \xi^{(l)}_{N_l+1} + \sum_{k=1}^{N_l} \alpha + \beta \xi^{(l)}_{k} \ln \xi^{(l)}_{k} \prod_{j=1, j \neq k}^{N_l+1} (1 - \xi^{(l)}_{j}) > \beta \xi^{(l)}_{k} \right] + \sum_{m \in L \setminus l} \beta \xi^{(m)}_{k} \right] \tag{4.7} \]

where

- \( L \) is the set of APs in the federated network.
- \( N_m \) represents the number of existing users in the cell of AP \( m, \forall m \in L \).
- The first part inside the square brackets of Eq.(4.7), i.e., \( \beta \xi^{(l)}_{N_l+1} \), represents the revenue gained from the incoming user.
- The second part inside the square brackets of Eq.(4.7) represents the revenue gained from the existing users of AP \( l \).
- The last part inside the square brackets of Eq.(4.7) represents the revenue gained from the other APs in the federated network.

The payoff is maximized when \( \exists l \in L \), and

\[ \alpha + \beta \xi^{(l)}_{k} \ln \xi^{(l)}_{k} \prod_{j=1, j \neq k}^{N_l+1} (1 - \xi^{(l)}_{j}) > \beta \xi^{(l)}_{k} \], \quad \forall k \in \{1, 2, ..., N_l + 1\} \tag{4.8} \]

From the set of first-choice APs, the CAS selects a local candidate where the user-chosen access probabilities can satisfy Eq.(4.8). If there are more than one first-choice AP that can accommodate the service request, the CAS chooses the one that could provide the maximum saturation throughput (i.e., \( \arg \max_{m \in L} \prod_{j=1}^{N_m} \left(1 - \xi^{(m)}_{j}\right) \)). In this way, the admission control procedure tries to associate each user to the most lightly loaded AP, hence maximizes the total utilization in the network. If there is no such local candidate, the CAS selects a remote candidate from the second-choice APs in the same way.
4.5 System Performance Evaluation

4.5.1 Evaluation Scenario

It is considered that the uplink of random access MAC where each user contends for channel access according to some user-chosen access probability. A transmission is successful if and only if there is a single transmission attempt - there is no carrier sensing, and no explicit back-off.

APs are deployed in a 300 m × 300 m square area as shown in Figure 4.4. Each AP locates at the central point of a 150 m × 100 m square area, which is termed home area hereafter. Each user arrives according to a Poisson process and stays for a time, which is exponentially distributed. Furthermore, two APs (i.e., AP 3 and AP 4) are selected to be heavily loaded APs. The arrival rate of users’ requests at the home area of the heavily loaded AP is twice higher than the arrival rates at the other home areas. Other detailed simulation settings are summarized as shown in Table 4.1.

<table>
<thead>
<tr>
<th>Table 4.1 Summary of the simulation settings.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Size of the square area</strong></td>
</tr>
<tr>
<td><strong>Number of APs</strong></td>
</tr>
<tr>
<td><strong>Transmission range of each AP</strong></td>
</tr>
<tr>
<td><strong>Maximum roaming distance (d)</strong></td>
</tr>
<tr>
<td><strong>Arrival rate at lightly loaded APs</strong></td>
</tr>
<tr>
<td><strong>Arrival rate at heavily loaded APs</strong></td>
</tr>
<tr>
<td><strong>Average stay duration</strong></td>
</tr>
<tr>
<td><strong>Raw bit rate</strong></td>
</tr>
<tr>
<td><strong>Constant ( \alpha )</strong></td>
</tr>
<tr>
<td><strong>Constant ( \beta )</strong></td>
</tr>
<tr>
<td><strong>Priority of user’s willingness to pay (( \theta ))</strong></td>
</tr>
<tr>
<td><strong>Access probability</strong></td>
</tr>
</tbody>
</table>

Algorithms termed no load balancing (NLB), network directed roaming (NDR) [4], and distributed myopic selection (DMS) [34], are used for comparison. In the NLB algorithm, users scan
Figure 4.4 Example of AP deployment.
all available channels and associate themselves to the AP that has the strongest RSSI. Therefore, the NLB algorithm offers little load balancing. In the NDR algorithm and the DMS algorithm, users can adapt themselves to roam and associate to the AP whose service could not be provided in place. If there are more than one AP that can accommodate the incoming user’s service request, the way of determining the optimal user-AP association in each algorithm can be summarized as shown in Table 4.2.

Table 4.2 Algorithms used for comparison.

<table>
<thead>
<tr>
<th>Alternative APs</th>
<th>The proposed algorithm</th>
<th>The NLB algorithm</th>
<th>The NDR algorithm</th>
<th>The DMS algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>APs within the roaming range of the user</td>
<td>APs whose transmission ranges can cover the user</td>
<td>APs within the roaming range of the user</td>
<td>APs within the roaming range of the user</td>
<td></td>
</tr>
<tr>
<td>AP which provides the maximum saturation throughput</td>
<td>AP with the strongest signal strength</td>
<td>AP with the shortest roaming distance</td>
<td>AP with the lowest cost [34]</td>
<td></td>
</tr>
</tbody>
</table>

4.5.2 Simulation Results

An important element in a load balancing system is the function used to evaluate the balance of the system. Comparing the throughput at different APs is not feasible, because the varying nature of the traffic generated by the stations always makes these values different. To explore the effect achieved by distributing load across the network, the concept balance index, firstly introduced in [62] and then used in [4], is adopted. Let $B_i$ be the total throughput of AP $i$, the balance index is defined as:

$$\gamma = \frac{(\sum B_i)^2}{(n \sum B_i^2)}$$

(4.9)
where \( n \) is the number of APs in the federated network. The balance index is 1 when all APs have exactly the same throughput, and tends to \( 1/n \) when the traffic load is severely unbalanced. The main target for a load balancing system is to maximize the balance index.

Figure 4.5 shows the balance index as a function of the simulation time. The curves show that the proposed algorithm has a larger performance gain even compared with the NDR algorithm and the DMS algorithm. This is not surprising because compared with the number of users in service, the permissible saturation throughput reflects the load level at each AP more properly. Hence, the load can be distributed across the federated network more evenly.

Figure 4.6 and Figure 4.7 show the blocking probability and the total throughput as a function of the simulation time, respectively. The curves show the effect of the proposed algorithm in terms of improving QoS. For instance, at the time of 30 min, the average blocking probabilities
Figure 4.6 Effect of the proposed algorithm in terms of improving QoS (blocking probability vs. simulation time).
Figure 4.7 Effect of the proposed algorithm in terms of improving QoS (throughput vs. simulation time).
are 0.155, 0.067, and 0.065 in the NLB algorithm, the NDR algorithm, and the DMS algorithm, respectively, and decrease to 0.062 in the proposed algorithm. Besides, the total throughput of six cells is 9.92 Mbps, 11.74 Mbps, and 11.87 Mbps in the NLB, the NDR, and the DMS algorithm, respectively, and increases to 12.01 Mbps in the proposed algorithm.

Figure 4.8 and Figure 4.9 show the number of users in service and total revenue as a function of the simulation time, respectively. The curves show the effect of the proposed algorithm in terms of increasing the total revenue of the federated network.

The cost of roaming depends upon the distance that the user has to travel to reach an AP that can accommodate the service request. To explore the tradeoff between the roaming distance and the effectiveness of the proposed algorithm, I simulate a network where the radius within which
4.5 System Performance Evaluation

Figure 4.9 Effect of the proposed algorithm in terms of increasing the total revenue of the federated network (total revenue vs. simulation time).
users could roam is progressively increased. The curves, plotted in Figure 4.10, show that the blocking probability decreases as the roaming radius increases and begins to level off at 160 m.

### 4.6 Concluding Remarks

In this study, a Stackelberg game structure is applied to obtain the equilibrium of bandwidth sharing between the CAS and the wireless users. The game is composed of three steps: (i) the CAS predefines a pricing scheme; (ii) users choose their access probabilities to optimize their payoffs, namely, best response strategies; (iii) the CAS uses the best response information to determine the AP-user association, which in turn maximizes its total revenue.

In order to exploit users’ mobility for load balancing, a remote AP can also be selected by the CAS. The remote AP with better QoS (i.e., saturation throughput) encourages the users to connect.
Hence, the load could be distributed across the federated network dynamically.

The performance of the proposed algorithm is evaluated via simulations. The observed results show that the proposed algorithm achieves greater or at least comparable balance and overall utilization, comparing to the best existing algorithms.
Chapter 5

Distributed Pricing and Connection Admission Control in WLANs

5.1 Introduction

As described previously, generally, there are two types of approaches to compensate the AP owners: centralized approach [4], [5] and decentralized approach [3], [6]. In the centralized approach, a third-party server is deployed to receive and process the service requests from users; while in the decentralized approach, users negotiate and pay the AP directly.

There are a number of benefits in using the centralized approach. Since a third-party server maintains the system state for all APs in the network, it can monitor and control the use of the wireless bandwidth in the network. Global knowledge of system state enables the server to easily identify heavily loaded APs and hence distribute users from a heavily loaded AP to a lightly loaded one.

The decentralized approach has its advantages as well. First, as the pricing process can be done in AP locally, there is no need for the AP to carry the user’s request traffic into the wired network for negotiation. This stops all unauthenticated traffic at the edge of the wired network and is thus a relatively low-risk design. Second, decentralization transfers decision-making processes to individual APs, thus reducing network management overhead and considerably increasing network scalability [8].

This study focuses on studying the properties of the decentralized approach. Without a third-
party server, the user and the private AP may not know each other’s identity, and may not be able to trust each other to carry out the transaction on each side. For example, a malicious AP might accept payment and then reject to deliver service when the user pays the AP in advance; on the other hand, a user may fail to make a promised payment after receiving service. Therefore, great care should be taken to structure the game in a way that prevents players from cheating. For example, one possible way would be for the user to pay the AP in small amounts over the duration of the session [63].

Many studies have focused on using pricing as an incentive mechanism to encourage the AP owners to share their networks with the public, where the overall payment charged grows with the time connected [51]. In [3], authors investigate the economic behaviours of wireless users under an assumption that the network has unlimited capacity. They prove that fixed rate is an optimal strategy to the wireless AP, given that users have a so-called "web browsing" utility function. The “web browsing” utility grows proportionally with the time slots he gains access initially, and saturates when he no longer intends to browse. In [6], authors think that it is only a special case that the network has unlimited capacity, or equivalently, has an adequate supply of bandwidth to meet all demands from users. The authors generalize the model in [3] by limiting the AP to admit at most $m > 0$ users at a time, and show that the elegant results in the unlimited capacity model (charging a fixed rate at all time) no longer apply. They propose an algorithm based on the Markovian decision theory [38] to devise the optimal pricing strategy.

The utility degradation of existing users, incurred by the admission of an incoming user, is not sufficiently considered in [3], [6]. Although limiting the AP to admit at most $m > 0$ users at a time [6] is more realistic, I argue that the limitation is a little bit strong. Actually, if the admission of the incoming "$m + 1$"-th user would increase the AP’s overall revenue, there is no reason to think that the AP will reject the incoming user.

As described in Section 2.1.2, connection admission control (CAC) is an important component for the maintenance of QoS [35], [36]. The purpose of CAC is to limit the amount of traffic admitted into a particular service class so that the level of QoS of the existing users will not be degraded, while at the same time the medium resources can be efficiently utilized.

In this study, the limitation that the AP admits at most $m$ number of users at a time, is relaxed, and a game theoretic approach is used to study the interaction among the AP and users. The AP first estimates the probable utility degradation of existing users consequent upon the admission of
an incoming user. Second, the AP decides: (i) whether the incoming user should be accepted; (ii) the price to be announced in order to maximize her revenue.

5.2 System Model

5.2.1 Unlimited-Capacity Model

The seminal work by Musacchio and Walrand [3] presents the economic behaviours of wireless users under a specific network topology. In particular, they prove that fixed rate pricing is optimal to the wireless AP, given that users have the "web browsing" utility function.

The model adopted by [3] is termed unlimited model. Note that the formulation of the unlimited model relies on a strong assumption that the channel capacity of the wireless network is unlimited and the AP has an unlimited uplink bandwidth to the Internet.

As shown in Figure 5.1, the interactions among the AP and the multiple users (i.e., including the incoming users and the existing users) are analyzed using a two-player game. Time is divided into slots. At the beginning of time slot $t$, a user sends a connection request over the slot. The AP replies with a slot price $p_t$. The user then chooses to accept the slot price and connect, or to reject and leave. The game ends: (i) when the user finds the slot price is too high to accept; or (ii) when the user does not intend to connect any more.

After the session of service, the user’s web browsing utility is:
\[ F(T, \tau) = U \min(T, \tau) \]  

(5.1)

where

- \( T \) is the number of time slots the user has connected;
- \( \tau \) is a discrete random variable representing the number of time slots the user intended to connect and browse the web;
- \( U \) is a continuous random variable representing the user's utility of gaining the Internet access in one time slot. The value of \( U \) is assumed to be fixed for that user during the service session.

Upon the end of the game, the user has a net payoff of \( F(T, \tau) - \sum_{t=1}^{T} p_t \), while the AP has a revenue of \( \sum_{t=1}^{T} p_t \). Authors in [3] prove that the following strategy profile is a PBE [47]:

- The user accepts the price and connects or remains connected in slot \( t \) if \( t < \tau \) and \( p_t \leq U \), otherwise the user rejects the price and leaves. (This is referred to as the myopic strategy.)
- The AP charges a non-decreasing price sequence \( p_t \) such that

\[ p_t \in \arg \max_p pP(U \geq p). \]

The set of maximizers of \( pP(U \geq p) \) is denoted by \( \arg \max_p pP(U \geq p) \). Note that the AP charges a fixed price sequence, since the expression \( pP(U \geq p) \) is maximized by a single price, which does not vary over time slots.

A PBE is simply a set of strategies and beliefs such that, at any stage of the game, the strategies are optimal under the given beliefs, and the beliefs are obtained from equilibrium strategies and observed actions. Namely, no player can increase the expected payoff by unilaterally deviating from the PBE strategy at any point in the game.
5.2 System Model

5.2.2 Limited-Capacity Model

The model I am envisioning assumes that each user communicates with a single AP directly. To maximize the system capacity and keep the interference to a minimum, neighboring APs (if exist) are configured to operate on different RF channels.

In order to clarify the relationship between the utility and the number of users associated with the AP, I turn to describe the 802.11 MAC layer protocol [20] and main characteristics of the wireless channel. The IEEE 802.11 WLAN specifies two medium access control mechanisms, i.e., distributed coordination function (DCF) and point coordination function (PCF) [64]. The basic access method in the IEEE 802.11 MAC protocol is DCF, which is based on carrier sense multiple access with collision avoidance (CSMA/CA). The other optional access method called PCF is only usable in infrastructure network configurations and is not supported in most of the current wireless cards. This study focuses on 802.11 DCF.

Each AP and the associated wireless users utilize only a single RF channel and use it as a shared spectrum resource. The spectrum is unlicensed and an unlimited number of users can share the spectrum with usage rights governed by technical standards. The CSMA/CA protocol, which is used for resolving contention among multiple users accessing the channel, allows wireless users to contend for transmission [64]. When two or more users want to transmit a packet at the same time, the packets collide and are lost; such packets become backlogged and must be retransmitted at a later time.

It has been shown experimentally and analytically that as the number of users associated with the AP increases, such random access networks lead to a degradation in QoS metrics including throughput, delay and packet loss rate [65], [66]. The utility of having the Internet access consequently decreases with the number of associated users increasing [67].

5.2.3 Utility Function

User $i$'s valuation of the access service is characterized by a utility $U_i^n$, where $n$ is the number of users associated with the AP. To focus on modelling, $U_i^n$ is given as follows.

$$U_i^n = \theta_i f(n)$$  \hspace{1cm} (5.2)

Here $\theta_i$ is a user-dependent scale factor and can be thought of as a parameter representing
Figure 5.2 Limited-Capacity model.

the priority of user \(i\)'s willingness to pay, also referred to as the utility rate. \(f(.)\) is a decreasing function of \(n\). This approach can also be applicable to more complex utility models which take into account the dynamics of the wireless environment, but these extensions are left for future work.

In summary, this model differs from the unlimited model in two ways: (i) the channel capacity of the wireless network here is limited; (ii) as shown in Eq.(5.2), the utility of each user varies as a function of the number of users associated with the AP. Figure 5.2 depicts this scenario.

**Lemma 2.** Considering users with utility defined by Eq.(5.2), it is no longer a PBE for the provider to charge all the users with a constant price per unit time.

**Proof.** It is assumed that there are \(n_t\) users associated in time slot \(t\), and \(n_{t+1}\) in time slot \(t+1\) (\(n_t \neq n_{t+1}\)). Therefore, the utility changes from \(U^{n_t}_i\) in time slot \(t\) to \(U^{n_{t+1}}_i\) in time slot \(t+1\). The price that the wireless AP picks to maximize the value of \(pP(U^{n_t}_i > p)\) in time slot \(t\) is no longer the maximizer of \(pP(U^{n_{t+1}}_i > p)\) in time slot \(t+1\).

\(\Box\)

### 5.3 Pricing and Connection Admission Control

#### 5.3.1 Micro Payment and Service Contract

Time is also divided into discrete slots or "periods". All users keep accurate common time (it is assumed that there exits a global clock or time synchronization mechanism). Each user pays the
5.3 Pricing and Connection Admission Control

AP in small payments over the course of the session.

During the session of service, although the AP would wish to cease service to users or increase the price over time to obtain higher revenue, it is reasonable to believe that users will be discouraged from buying such a kind of service since the break of service might disturb users’ applications, and it is unrealistic to require users to monitor the varying price continuously [6]. Therefore, it is assumed that the AP cannot change the price during the session of service, and that the AP cannot suspend the service as long as the user can keep paying, while the user can disconnect voluntarily. The contract between an AP and a user is described as follows.

- The AP provides access service for the user until the user voluntarily disconnects;
- The user pays a price for the obtained service. The total payment is the price times the duration of the service.

Note that the AP is allowed to announce different prices to different users, but once announced, the price cannot be changed over the duration of the session.

The pricing and CAC processes are executed one user after another according to their arrival time. Users are named according to their arrival order.

5.3.2 Steps Involved in Negotiation

As shown in Figure 5.3, an incoming user tries to start a session by initially sending a connection request to the AP. The AP who receives the request, decides whether the incoming user should be accepted. Intuitively, when the network is overloaded, the AP rejects the connection request. Otherwise, the AP accepts the connection request and announces a slot price based upon a certain kind of revenue maximization. On the other hand, at the beginning of each time slot, the user chooses to accept the slot price and connect (or keep connecting) to the AP, or to reject and leave. The game ends at the first time the user rejects the AP’s proposal.
Figure 5.3 Diagram showing the sequence of steps involved in pricing and connection admission control.
5.4 Multi-Stage Non-Cooperation Game, and Revenue Maximization

5.4.1 Strategy Space

Under the limited-capacity model, the utility of having the Internet access decreases with the number of users associated with the AP increasing. In case that the utility decreases below the price charged, the existing users may reject the price and leave. The disconnections of existing users incur revenue loss. This imposes the AP a capacity constraint on her revenue maximization problem.

Therefore, in order to maximize her overall revenue, the AP has to decide the price for the incoming user based on not only the revenue growth from the admission of an incoming user, but also the potential revenue loss incurred by the quitting of existing users. To be precisely, the revenue growth from the incoming user should at least compensate for the revenue loss incurred by the quitting of existing users. Otherwise, the AP should reject the connection request.

Let \( n_t (n_1 = 0) \) represent the number of users that keep connected at the beginning of time slot \( t \). Let \( m_t (m_1 = 0) \) represent the overall number of admitted users before time slot \( t \). Furthermore, let \( \Delta n_t \) be the number of users that are newly admitted in time slot \( t \). \( m_{t+1} \) equals to \( m_t + \Delta n_t \).

In order to more carefully examine the notion of incentives in the network described above, the access sharing problem is formulated as a multi-stage non-cooperation game, where the players of the game are the AP and users.

As depicted in Figure 5.4, a pure strategy for the AP can be specified by a sequence of non-negative prices \( \{ \{ p_i \} \}_{t=m_{t+1}}^{m_{t+1}+1} \) (hereafter termed \( \{ p_i \}_{t=1}^\infty \) for simplicity) to maximize her overall revenue. When \( \Delta n_t \) equals to 0, \( \{ p_i \}_{i=m_{t+1}}^{m_{t+1}+1} \) is \( \emptyset \), since no decision should be made in time slot \( t \).

User \( i \)'s type is specified by the priority of his willingness to pay \( \theta_i \), the arriving slot \( \tau_{i0} \) and the intended terminating slot \( \tau_{i1} \). The user knows the values for \( \theta_i \), \( \tau_{i0} \) and \( \tau_{i1} \), while the AP just knows the value of \( \tau_{i0} \) as well as the distributions of \( \theta_i \) and \( \tau_{i1} - \tau_{i0} \).

Since the AP does not know the type-information of users (e.g., \( \theta_i \) and \( \tau_{i1} - \tau_{i0} \)) exactly, the AP has to induce the type-information based on the history of users’ choices. For instance, whenever a myopic user \( i \) accepts the price \( p_i \) while the number of users associated with the AP is \( n \), the AP can confine \( \theta_i \) by lower bounding it with \( p_i / f(n) \), i.e., the AP believes that user \( i \) would definitely accept the price \( p_i \) once the number of users associated with the AP is less than \( n \).
### 5.4.2 Perfect Bayesian Equilibrium

**Lemma 3.** Under the limited-capacity model, the following strategy profile is a PBE.

- Existing user $i \in \{1, 2, \ldots, m_t\}$, remains connected in slot $t$, if and only if $\tau_i^1 > t$ and $U_i^{m_t} > p_i$.

- The "$k$"-th incoming user in slot $t$, $k \in \{1, 2, \ldots, \Delta n_t\}$, connects if $U_{m_t+k}^{m_t} > p_{m_t+k}$. (This is referred to as the myopic strategy.)

- The AP charges the incoming users in slot $t$ with a sequence of prices $\{p_{m_t+k}\}$, $k \in \{1, 2, \ldots, \Delta n_t\}$ as follows.

$$p_{m_t+k} \in \arg \max_{p \in \mathbb{R}^+} pP(U_{m_t+k}^{m_t+k} > p) \quad (5.3)$$

---

**Figure 5.4** Strategy space for the AP.

- **Strategies:** $\{p_i\}_{i=1}^{m_1}$, $\{p_i\}_{i=m_1+1}^{m_2}$, $\ldots$, $\{p_i\}_{i=m_{t-1}+1}^{m_t}$
- **States:** $n_1 = 0$, $n_2$, $n_3$, $n_t$, $\ldots$, $m_1$, $m_2$, $m_3$, $\ldots$, $m_t$
- **Time:** Slot 1, Slot 2, Slot $t$

![Figure 5.4 Strategy space for the AP.](image-url)
subject to the constrain shown in Eq. (5.4).

\[ p_{m_t+k} P(U_{m_t+k}^{n_t+k} > p_{m_t+k}) \]

\[ \sum_{s=t+1}^{\infty} P(\tau_{m_t+k}^l > s | \tau_{m_t+k}^l > t) \]

\[ > \sum_{i=1}^{m_t} \left[ P(U_i^{\max(n_t+k-1,n_i^{\max})} > p_i) - P(U_i^{\max(n_t+k,n_i^{\max})} > p_i) \right] \frac{p_i}{P(U_i^{\tau_i^l} > p_i)} \]

\[ \sum_{s=t+1}^{\infty} P(\tau_i^l > s | \tau_i^l > t) \]

\[ + \sum_{i=m_t+1}^{m_t+k-1} \left[ P(U_i^{n_t+k-1} > p_i) - P(U_i^{n_t+k} > p_i) \right] \frac{p_i}{P(U_i^{n_t+k-m_t} > p_i)} \]

\[ \sum_{s=t+1}^{\infty} P(\tau_i^l > s | \tau_i^l > t), \]

\[ k \in \{1, 2, ..., \Delta n_t\} \]

- \( p_{m_t+k} \) is the price for the "k"-th incoming user in slot \( t \);
- \( P(U_{m_t+k}^{n_t+k} > p) \) is the probability that the utility of gaining access is higher than the rate \( p \);
- for any \( p \in \mathbb{R}^+ \), the set of maximizers of \( pP(U_{m_t+k}^{n_t+k} > p) \) is denoted by \( \arg\max_p pP(U_{m_t+k}^{n_t+k} > p) \);
- \( n_i^{\max} \), which is hereafter termed congestion tolerance, indicates the historical knowledge that the user \( i \) chooses to keep connected when the network gets the most congested after his connection. Note that \( n_i^{\max} \) equals to \( \max_{u \in \{ \tau_i^0, ..., \tau_i^{t-1} \}} n_u \).

**Proof.** Please refer to Appendix B for the details of proof. \( \square \)

Lemma 3 suggests that an AP should pick an optimal price to gain as much as possible from an incoming user (i.e., Eq. (5.3)), while checking whether the revenue growth from the incoming user can compensate for the revenue loss due to the disconnections of existing users (i.e., Eq. (5.4)).
When the expected revenue growth from the incoming user cannot compensate for the revenue loss, the network is considered to be not having enough capacity for accommodating the incoming user’s service request. In this case, the network is marked as overloaded. Otherwise, the AP accepts the connection request and announces a slot price based upon a certain kind of revenue maximization.

5.4.3 A Closed-Form Solution

In this section, a solution for the optimal rate to be charged is investigated as an instance. For simple calculations, it is assumed that user \( i \)'s utility rate \( \theta_i \) has uniform distribution on an interval \([a, b] \), and \( U^n_i = \theta_i / n \). Furthermore, it is assumed that user \( i \) stays for a time which is exponentially distributed.

The objective function \( L(p) \) is defined in Eq.(5.5) as follows.

\[
L(p) = p P(U^m_{i+k} > p) = \frac{b - (n_t + k)p}{b - a} \tag{5.5}
\]

To obtain the maximum of \( L(p) \), I take the derivative of \( L(p) \) with respect to \( p \) and let it equal to 0, i.e., \( L'(p) = 0 \). I have \( p = \frac{b}{2(n_t + k)} \). Furthermore, if taking the second derivative of \( L(p) \) with respect to \( p \), I get \( L''(p) < 0 \), which suggests that the function is concave down at \( p \). Thus, in order to maximize \( L(p) \), the AP charges user \( m_t + k \) with the following rate:

\[
p_{m_t+k} = \frac{b}{2(n_t + k)} \tag{5.6}
\]

According to Lemma 3, the complementary condition Eq.(5.4) should be satisfied in order to maximize the overall revenue. Here, Eq.(5.4) can be transformed into the following expression:

\[
\frac{b^2}{4(b - a)(n_t + k)} \sum_{s=t+1}^{\infty} P(\tau^1_{m_t+k} > s | \tau^1_{m_t+k} > t) \\
> \sum_{i=1}^{m_t} \frac{\max(n_t + k, n_{i,d}^{\text{max}}) - \max(n_t + k - 1, n_{i,d}^{\text{max}})}{b - n_{i,d}^{\text{max}} \cdot p_i} p_i^2 \\
\sum_{s=t+1}^{\infty} P(\tau_i^1 > s | \tau_i^1 > t) \\
+ \sum_{i=m_t+1}^{m_t+k-1} \frac{p_i^2}{b - n_{i,d}^{\text{max}} \cdot p_i} \sum_{s=t+1}^{\infty} P(\tau_i^1 > s | \tau_i^1 > t) \tag{5.7}
\]
Note that $\tau_i^1 - \tau_i^0$ represents the stay duration of user $i$, which is assumed to be exponentially distributed. Using the memorylessness property of exponential distribution, I have

\[
P(\tau_i^1 > s | \tau_i^1 > t) = P(\tau_i^1 - \tau_i^0 > s - t | \tau_i^1 - \tau_i^0 > t - t_i^0) = P(\tau_i^1 - \tau_i^0 > s - t)
\]

\[\forall i \in \{1,2,\ldots,m_t+k\}\] (5.8)

Eq.(5.7) can therefore be transformed into Eq.(5.9).

\[
b^2 \\
\frac{4(b-a)(n_t+k)}{m_t + k} \left( \max(n_t + k, n_{i,t}^{\text{max}}) - \max(n_t + k - 1, n_{i,t}^{\text{max}}) \right) - n_{i,t}^{\text{max}} p_i \\
+ \sum_{i=m_t+1}^{m_t+k-1} \frac{p_i^2}{b - n_{i,t}^{\text{max}} p_i}
\] (5.9)

A binary indicator $x_{i,t}$ is defined as follows.

\[
x_{i,t} = \begin{cases} 
1 & \text{if } n_t + k > n_{i,t}^{\text{max}}, \\
0 & \text{otherwise}.
\end{cases}
\] (5.10)

Then Eq.(5.9) is transformed into Eq.(5.11).

\[
b^2 \\
\frac{4(b-a)(n_t+k)}{m_t + k} \sum_{i=1}^{m_t+k-1} \frac{x_{i,t} p_i^2}{b - n_{i,t}^{\text{max}} p_i}
\] (5.11)

When the complementary condition Eq.(5.11) is not tenable, i.e., the revenue growth from the incoming user is not enough to compensate for the revenue loss due to the utility degradation of existing users, the AP rejects the connection; otherwise, the AP announces a price according to Eq.(5.6).

According to Eq.(5.6), the AP would decrease the price when the network is heavily loaded, and increase the price when the network is lightly loaded. Existing users may monitor the varying price dynamically, and deliberately adopt the "disconnection-and-renegotiation" strategy in order to gain a lower price. However, the interrupted access service as well as the risk of being rejected in renegotiation process would prevent the existing users from being a speculator. For the anti-speculator issues, it is out of the scope of this research, and I treat it as the future work.
For experimental evaluation, simulations have been conducted. A model of a public-area WLAN is constructed, where users arrive according to a Poisson process at rate $\lambda$ per hour, and stay for a time which is exponentially distributed with an average time of $\gamma$ hours. The load of users’ requests is therefore set to $\lambda \times \gamma$. Furthermore, let $\theta_i$ be uniformly distributed on the interval $[0,200]$. The length of a slot is set to 0.5 hour. Each simulation lasts 24 hours, and is repeated for 5000 times.

The curves in Figure 5.5, show the blocking probability as a function of the number of users associated with the AP and the average congestion tolerance of existing users. On the other hand, the curves in Figure 5.6, show the blocking probability as a function of the average price and the
Figure 5.6 Blocking probability in terms of the number of users associated with the AP, price and average congestion tolerance (blocking probability vs. price and congestion tolerance).
Figure 5.7 Overall revenue in terms of arrival rate (average stay duration = 0.5 hour).

average congestion tolerance of existing users. The arrival rate here is set to 15 per hour, and the average stay duration is set to 1 hour. It can be observed that

- The less the number of users associated with the AP is, the lower probability with which the AP blocks the new connection.

- The higher congestion tolerance the existing users have, the lower probability with which the AP blocks the new connection.

- The lower price the existing users are bound with, the lower probability with which the AP blocks the new connection.

In order to explore the effect of the proposed algorithm on increasing AP’s revenue, the fixed rate scheme which offers little CAC is used for comparison. In particular, the fixed rate is set to
Figure 5.8 Overall revenue in terms of arrival rate (average stay duration = 1.0 hour).
Figure 5.9 Overall revenue in terms of arrival rate (average stay duration = 1.5 hour).
5.5 Concluding Remarks

10, 30, 50, 70 and 90, respectively. The distinction between the two schemes is that: the proposed scheme examines the potential revenue loss before accepting an incoming user, while the other one accepts all users straightforwardly.

In Figure 5.7, Figure 5.8 and Figure 5.9, the average stay duration is set to 0.5 hour, 1 hour, and 1.5 hours, respectively. The arrival rate here varies from 1 per hour to 20 per hour. The curves show that the proposed algorithm outperforms its counterpart in terms of increasing AP’s revenue.

This study has proposed a distributed pricing scheme in conjunction with a CAC policy for revenue maximization in WLANs. First, the interactions among the AP and wireless users have been modelled as a multi-stage non-cooperative game. Afterwards, the stability of the proposed scheme in terms of convergence to a PBE has been studied. In the PBE, the AP cannot increase the revenue by unilaterally deviating from the PBE strategy at any point in the game. Simulation results have revealed that the proposed scheme outperforms the conventional fixed rate pricing scheme in terms of increasing AP’s revenue.
Chapter 6

Conclusions and Future Work

6.1 Overview of Research Achievements

According to the current state of the art and the future requirement in pricing and congestion control as that has been discussed in Chapter 1, this dissertation has tried to solve the opening issues by proposing following major novel contents:

- Auction-based pricing and resource sharing;
- Stackelberg-game modelling of pricing and load distribution with QoS differentiation;
- Distributed pricing and connection admission control for revenue maximization.

In Chapter 3, the study focused on learning the economic behaviours of the APs within a federated network, and using a game theoretic approach to analyze the interactions among them. It has been proven that for each AP that accurately broadcasts her cost of access, it results in convergence to a Nash equilibrium solution. The efficiency of the Nash equilibrium solution is evaluated via simulations. The proposed algorithm decreases the degree of blocking probability in the system, and improves the degree of social welfare in the system in comparison to the existing fixed rate and fixed rate with roaming schemes.

In Chapter 4, a Stackelberg game structure was applied to obtain the equilibrium of bandwidth sharing amongst users through negotiation between the CAS and the wireless users. The game is composed of three steps: (i) the CAS predefines a pricing scheme; (ii) users choose their access
probabilities to optimize their payoffs, namely, best response strategies; (iii) the CAS uses the best response information to determine the AP-user association, which in turn maximizes its total revenue. In order to exploit users’ mobility for load balancing, a remote AP can also be selected for each user by the CAS. The remote AP with better QoS (i.e., saturation throughput) encourages the users to connect. Hence, the load could be distributed across the federated network dynamically. The performance of the proposed algorithm is evaluated via simulations. The observed results show that the proposed algorithm achieves greater or at least comparable balance and overall utilization, comparing to the best existing algorithms.

In Chapter 5, a decentralized pricing scheme in conjunction with a CAC policy has been proposed for revenue maximization in WLANs. The proposed CAC policy is completely distributed and can be implemented by individual APs using only local information. First, the interactions among the AP and wireless users are modelled as a multi-stage non-cooperative game. Then the stability of the proposed scheme in terms of convergence to a PBE is studied. In the PBE, the AP cannot increase the revenue by unilaterally deviating from the PBE strategy at any point in the game. Simulation results have revealed that the proposed scheme outperforms the conventional fixed rate pricing scheme in terms of increasing AP’s revenue.

The pricing and congestion control algorithms are designed from an economic point of view. This dissertation contributes to a deep understanding of the interactions among users. Furthermore, the analysis presented in this work constitutes a theoretical foundation for incentive-compatible CAC in WLANs. Simulation results show that the proposed algorithms achieve better or at least comparable overall resource utilization and QoS performance, comparing with the best existing algorithms.

The approaches proposed in Chapter 3 and Chapter 4 are centralized approaches, while the approach proposed in chapter 5 is a decentralized approach. Main contributions of this dissertation could be summarized as shown in Figure 6.1.
6.1 Overview of Research Achievements

Figure 6.1 Main contributions of the dissertation.

Contributions

Centralized approach
- Revenue maximization
- Hot-spot congestion relief
- Load balancing

Decentralized approach
- Revenue maximization
- Connection admission control
6.2 Discussion of Centralized Approach and Decentralized Approach

There are a number of benefits in using the centralized approach. Since a third-party server maintains the system state for all APs in the network, it can monitor and control the use of the wireless bandwidth in the network. As presented in Chapter 4, global knowledge of the price information of each AP enables the server to identify the cost-efficient AP for each user, and hence improve the resource utilization. Furthermore, global knowledge of system state enables the server to easily identify heavily loaded APs and hence distribute users from a heavily loaded AP to a lightly loaded one. Nevertheless, since the state must be maintained by the central server for each AP, as the number of AP increases so does the overhead. Therefore, it is doubted that the centralized approach cannot be able to scale to, for example, millions of users and thousands of APs.

The implementation of this type of approach requires a major structural changes not only to network management but also to users’ applications. Boingo network [2] is such an example. Boingo network secures roaming agreements with more than 100 different network operators around the world, and provides roaming software that can be private-labeled or integrated into the existing application to extend the current service offering to include more than 600,000 APs around the world.

The decentralized approach has its advantages and disadvantages as well. First, as the pricing process can be done in AP locally, there is no need for the AP to carry the user’s traffic into the wired network for negotiation. This stops all unauthenticated traffic at the edge of the wired network and is thus a relatively low-risk design. Second, decentralization transfers decision-making processes to individual APs, thus reducing network management overhead and considerably increasing network scalability. However, when the AP cannot accommodate the user’s service request, no information could be provided to the incoming user for applying services somewhere else, which may discourage the usage.

Several open issues should also be addressed before integrating the proposed decentralized approach into real networks. First, congestion-based prices of the decentralized approach are quoted in realtime to users. The users may be discouraged from buying such a kind of service since it is unrealistic for them to monitor the varying price continuously. However, it is possible to imagine an automated decision-making process that would employ artificial intelligence to make the ser-
### Table 6.1
Main advantages and disadvantages of each of centralized and decentralized approach.

<table>
<thead>
<tr>
<th>Advantage</th>
<th>Disadvantage</th>
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<td><strong>Centralized approach</strong></td>
<td><strong>- Increased network management complexity</strong></td>
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<tr>
<td>- Can play a role in congestion relief</td>
<td>- Increased fairness</td>
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<td>- Increased fairness</td>
<td>- Scalability problem</td>
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<td><strong>Decentralized approach</strong></td>
<td><strong>- Increased billing complexity</strong></td>
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<td>- Relatively low-risk design</td>
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<tr>
<td>- Little overhead for network management</td>
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vice choice decision based on current prices. Second, without a third-party server, the user and the AP may not know each other’s identity, and may not be able to trust each other to carry out the transaction on each side. For example, a malicious AP might accept payment and then reject to deliver service when the user pays the AP in advance; on the other hand, a malicious user may fail to make a promised payment after receiving service. Therefore, great care should be taken to structure the game in a way that prevents players from cheating. It is possible to envision a futuristic scenario where QoS levels with arbitrarily fine granularity are available to all wireless users, where prices are determined in order to maximize the overall revenue, and where users are billed for network usage in real time using micro-payment systems developed for e-commerce. The centralized approach proposed in this dissertation lays a groundwork toward this futuristic scenario.

A brief summary of the main advantages and disadvantages of each of centralized and decentralized approach is presented in Table 6.1.

### 6.3 Future Work

In this dissertation, several assumptions made may be considered unrealistic or complex (e.g., the ability of the CAS to estimate the physical roaming cost, and the ability to direct users to the indicated APs). It is worth pointing out that the main scope of these studies is to demonstrate the feasibility of an incentive-compatible load distribution approach for a federated network. The
detailed description of a realistic implementation and security concerns is beyond the scope of this dissertation and it represents the next step of this research activity.

Furthermore, the analysis in this dissertation focuses on the access network merely. The revenue distribution between the access network and the core network can be a concern as well. Since the revenue distribution does not change the structure of game modelling, the analysis and corresponding results can be easily extended to the model including the core network.

Precise modelling of user behaviour is the most critical part of the pricing problem. Assuming a given utility function may result in an oversimplification of the complexities of user behaviour. Ideally, utility should be expressed as a function of actual QoS metrics, such as throughput, delay and packet loss rate. In most real networks, however, it is impossible to predict such QoS metrics in advance, since the QoS metrics are closely dependent upon factors such as traffic models, scheduling disciplines and network topology. Therefore, a simple MAC model is employed to abstract out the essential features of QoS-aware MAC, so as to predict the saturation throughput. In this fashion, the utility still indicates a user’s sensitivity to changes in QoS.

Future work also includes the extension of distributed CAC algorithm to multi-AP scenarios, in which the rejected users could associate themselves to other APs through channel switching or network directed roaming.
Appendix A

Proof of Lemma 1

Before proceeding to the proof for Lemma 1, I first prove Sublemma 1 and Sublemma 2 that will support the proof. Furthermore, the proof focuses on the case 1 listed in Section 3.3, while omitting the other cases. It is easy to follow the after-mentioned proof to prove the other cases similarly. For $i = 1, \ldots, S$, the payoff function $P_i$ for AP $i$ is shown in Eq. (A.1).

$$
P_i = \begin{cases} 
    \min_{j \neq i} (s_j + x_j w_0) - x_i w_0 - c^i_k & \text{if } s_i < \min_{j \neq i} (s_j + x_j w_0) - x_i w_0, \\
    0 & \text{otherwise.}
\end{cases}
$$

(A.1)

**Sublemma 1.** As shown in Figure A.1, when $\min_{j \neq i} (s_j + x_j w_0) - x_i w_0 < c^i_k$, the strategy of underbidding (i.e., $s_i < c^i_k$) is dominated by bidding truthfully (i.e., $s_i = c^i_k$).

**Proof.**

- When $s_i < \min_{j \neq i} (s_j + x_j w_0) - x_i w_0 < c^i_k$ (i.e., $s_i$ exists in the area marked with slash lines in Figure A.1), then AP $i$ would be the AP that offers the lowest price and the payoff would be negative (i.e., $\min_{j \neq i} (s_j + x_j w_0) - x_i w_0 - c^i_k$).

- Otherwise (i.e., $\min_{j \neq i} (s_j + x_j w_0) - x_i w_0 < s_i < c^i_k$, $s_i = c^i_k$ or $s_i > c^i_k$), AP $i$ would not be the AP that offers the lowest price. The payoff would be 0. Furthermore, the bid’s amount does not change the payoff.

Therefore, when $\min_{j \neq i} (s_j + x_j w_0) - x_i w_0 < c^i_k$, the strategy of underbidding may lead to a negative payoff, while strategy of bidding truthfully will get a 0 payoff. $\square$
Chapter A Proof of Lemma 1

Sublemma 2. As shown in Figure A.2, when $\min_{j \neq i}(s_j + x_jw_0) - x_iw_0 > c^i_k$, the strategy of overbidding (i.e., $s_i > c^i_k$) is dominated by bidding truthfully (i.e., $s_i = c^i_k$).

Proof. 

- When $s_i > \min_{j \neq i}(s_j + x_jw_0) - x_iw_0 > c^i_k$ (i.e., $s_i$ exists in the area marked with slash lines in Figure A.2), then AP $i$ would not be the AP that offers the lowest price. The payoff would be 0.

- Otherwise (i.e., $\min_{j \neq i}(s_j + x_jw_0) - x_iw_0 > s_i > c^i_k$, $s_i = c^i_k$ or $s_i < c^i_k$), then AP $i$ would be the AP that offers the lowest price. The payoff would be positive (i.e., $\min_{j \neq i}(s_j + x_jw_0) - x_iw_0 - c^i_k$). Furthermore, the bid’s amount does not change the payoff.

Therefore, when $\min_{j \neq i}(s_j + x_jw_0) - x_iw_0 > c^i_k$, the strategy of overbidding may lead to a 0 payoff, while the strategy of bidding truthfully will get a positive payoff.

Since announcing the cost truthfully ensures a AP the highest payoff, the AP would not cheat.
with adventure. For each AP, announcing her cost truthfully for the item converges to a Nash Equilibrium solution.
Appendix B

Proof of Lemma 3

Lemma 3 is proved by verifying that the strategy profiles remain the best responses to each other in any continuation game, beginning from an arbitrary slot $t$ as follows.

Proof. First, the AP’s optimal counter strategy to a user playing the myopic strategy should be found. A pure strategy for the AP can be specified by a sequence of non-negative prices $\{p_i\}_{i=1}^{\infty}$ to charge the "$i$"-th incoming user. The AP chooses her sequence of prices to maximize her overall revenue, i.e., $\mathcal{J}(\{p_i\}_{i=1}^{\infty})$, as shown in the Eq.(B.1):

$$
\max_{\{p_i\}} \mathcal{J}(\{p_i\}_{i=1}^{\infty}) = \max_{\{p_i\}} \left\{ \sum_{i=1}^{\infty} \left[ \sum_{m_i}^{m_i+\Delta n_i} P(U_{i t}^m > p_i U_{i t}^{\text{max}} > p_i) p_i P(\tau_i^1 > t) \right. \right. \\
\left. \left. \quad + \sum_{i=m_i+1}^{m_i+\Delta n_i} P(U_{i t}^{m_i+i-m_i} > p_i) p_i P(\tau_i^1 > t) \right] \right\}
$$

(B.1)

where

- $P(U_{i t}^m > p_i U_{i t}^{\text{max}} > p_i)$ is the probability that the existing user $i$ keeps connected in time slot $t$, under the condition that the user $i$ chooses to keep connected when the network gets the most congested after his connection;

- $P(\tau_i^1 > t)$ is the probability that user $i$ is intended to connect in time slot $t$. 

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Chapter B Proof of Lemma 3

• $\sum_{i=1}^{m_t} P(U_{i}^{m_t} > p_i | U_{i}^{\tau_i} > p_i) p_i P(\tau_i > t)$ represents the revenue received from the existing users in time slot $t$;

• $\sum_{i=m_t+1}^{m_t+\Delta m_t} P(U_{i}^{m_t+i-m_t} > p_i) p_i P(\tau_i > t)$ represents the revenue received from the incoming users in time slot $t$.

At the beginning of time slot $t$, since the sequence of prices $\{p_i\}_{i=1}^{m_t}$ has already been decided, the AP only has to choose a sequence of prices $\{p_i\}_{i=m_t+1}^{m_t+\Delta m_t}$ to maximize her revenue. When the incoming user is admitted, the revenue growth received from the "k"-th incoming user is denoted by $R_{m_t+k}^{\text{growth}}(p)$, and the revenue loss received from existing users is denoted by $R_{m_t+k}^{\text{loss}}$. Therefore, finding the solution for Eq.(B.1) is transformed into solving Eq.(B.2) under the condition of Eq.(B.3).

$$p_{m_t+k} \in \arg\max_p R_{m_t+k}^{\text{growth}}(p)$$

subject to

$$R_{m_t+k}^{\text{growth}}(p_{m_t+k}) > R_{m_t+k}^{\text{loss}}$$

where $R_{m_t+k}^{\text{growth}}(p_{m_t+k})$ and $R_{m_t+k}^{\text{loss}}$ are given as follows.

$$R_{m_t+k}^{\text{growth}}(p_{m_t+k}) = \sum_{s=t+1}^{\infty} [P(U_{m_t+k}^{s-m_t+k} > p_{m_t+k}) P_{m_t+k}$$

$$P(\tau_{m_t+k}^1 > s | \tau_{m_t+k}^1 > t)]$$

On the other hand,

$$R_{m_t+k}^{\text{loss}} = R_{m_t+k}^{\text{reject}} - R_{m_t+k}^{\text{accept}}$$

where $R_{m_t+k}^{\text{reject}}$ represents the revenue received from the existing users when the incoming user is not admitted. $R_{m_t+k}^{\text{accept}}$ represents the revenue received from the existing users when the incoming user
is admitted. $R_{m_t+k}^{\text{reject}}$ is given as Eq.(B.6).

$$
R_{m_t+k}^{\text{reject}} = \sum_{s=t+1}^{\infty} \left\{ \sum_{i=1}^{m_t} \left[ P(U_i^{m_t+k-1} > p_i \mid U_i^{\text{max}} > p_i) P(\tau_i^1 > s \mid \tau_i^1 > t) \right] 
+ \sum_{i=m_t+1}^{m_t+k-1} \left[ P(U_i^{m_t+k-1} > p_i \mid U_i^{m_t+i-m_t} > p_i) P(\tau_i^1 > s \mid \tau_i^1 > t) \right] \right\} \quad (B.6)
$$

$$
k \in \{1, 2, ..., \Delta n_t\}
$$

Similarly, $R_{m_t+k}^{\text{accept}}$ is given as Eq.(B.7).

$$
R_{m_t+k}^{\text{accept}} = \sum_{s=t+1}^{\infty} \left\{ \sum_{i=1}^{m_t} \left[ P(U_i^{m_t+k} > p_i \mid U_i^{\text{max}} > p_i) P(\tau_i^1 > s \mid \tau_i^1 > t) \right] 
+ \sum_{i=m_t+1}^{m_t+k-1} \left[ P(U_i^{m_t+k} > p_i \mid U_i^{m_t+i-m_t} > p_i) P(\tau_i^1 > s \mid \tau_i^1 > t) \right] \right\}, \quad (B.7)
$$

$$
k \in \{1, 2, ..., \Delta n_t\}
$$

Eq.(B.2) and Eq.(B.3) can therefore be transformed into Eq.(5.3) and Eq.(5.4) respectively.

Note that \( \arg \max_p pP(U_{m_t+k}^{m_t+k} > p) \) is non-empty because \( y(p) = pP(U_{m_t+k}^{m_t+k} > p) \) is a continuous, non-negative function, with \( y(0) = 0 \), and \( \lim_{p \to \infty} y(p) = 0 \), and thus must achieve a maximum on \([0, \infty)\).

Now looking at the user’s side, it is not difficult to notice that the myopic strategy is the best response to an AP. As incoming users connect, each existing user’s utility decreases consequently. Once the utility decreases below the price charged, without the voluntary disconnections of other users, the user should never expect that his negative-payoff condition could take a favourable turn in the next time slot.
Bibliography


### List of Academic Achievements

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