Integration of WiMAX and WiFi: Optimal Pricing for Bandwidth Sharing

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ABSTRACT

Broadband wireless access networks based on WiMAX can provide backhaul support for mobile WiFi hotspots. We consider an integrated WiMAX/WiFi network for such an application where the licensed WiMAX spectrum is shared by the WiFi access points/routers to provide Internet connectivity to mobile WiFi users. The WiMAX backbone network and WiFi hotspots are operated by different service providers. Issues such as protocol adaptation, quality of service support, and pricing for bandwidth sharing that are related to integration of these networks are discussed. In addition, we propose a model for optimal pricing for bandwidth sharing in an integrated WiMAX/WiFi network. A Stackelberg leader-follower game is formulated to obtain the optimal pricing solution for bandwidth sharing. Performance evaluation results reveal some interesting insights into the problem.

INTRODUCTION

WiMAX has emerged as a promising technology for broadband access in wireless metropolitan area network (WMAN) environment. One of the potential applications of WiMAX is to provide backhaul support for mobile WiFi hotspots. Traditionally, a WiFi hotspot is connected to the Internet via a wired connection (e.g., digital subscriber line, DSL). However, by using an IEEE 802.16e/WiMAX-based backbone network to connect WiFi hotspots to the Internet, costly wired infrastructure can be avoided, and, again, mobile hotspot services can be provided (e.g., for intelligent transportation system [ITS] applications).

We consider a system model shown in Fig. 1. In this model a WiMAX base station (BS) operating in a licensed band serves both WiMAX subscriber stations (SSs) and WiFi access points (APs)/routers in its coverage area. The connection between the BS and an SS is dedicated to a single user (which is presumably shared among multiple sessions), while the connection between the AP/router and the BS is shared among the wireless LAN (WLAN) nodes. Also, the WiMAX BS and WiFi APs/routers are assumed to be operated by different service providers. Each of the SSs has a fixed bandwidth demand from the BS, while the APs/routers have elastic (i.e., time-varying) demand.

In this article we first discuss the issues of protocol adaptation, quality of service (QoS) provisioning, and pricing for resource allocation in an integrated WiMAX/WiFi network. The pricing issue is particularly emphasized. While radio resource management schemes such as traffic scheduling, rate and power allocation, and admission control determine how the limited radio resource is used, the pricing scheme controls the amount of radio resource usage by network subscribers. The resource allocation/sharing mechanism in an integrated WiMAX/WiFi network would be closely related to the pricing model used. A pricing scheme aims at maximizing the system utility, which is a function of the network QoS requirements. We review different approaches to pricing in wireless networks and their applicability in an integrated WiMAX/WiFi environment.

To this end, we propose an optimal pricing scheme for bandwidth sharing in an integrated WiMAX/WiFi network. For the network model described above, the WiMAX and WiFi service providers have to negotiate with each other to determine the optimal price such that their profits are maximized. We use game theory to analyze and investigate this problem. The WiMAX BS is the major player in this game—its decision on pricing for bandwidth sharing influences the decision of the WiFi APs/routers. Therefore, we consider this as a Stackelberg leader-follower game in which the WiMAX BS and the WiFi routers are the leader and the followers, respectively. The payoff for this game considers an elastic bandwidth demand function due to the time-varying demand from the WiFi nodes. For the solution of this game, we consider a Stackelberg equilibrium in which the payoff of the leader is maximized, and all the followers choose their best responses given the strategy of the leader. In addition, since in an actual system information on bandwidth demand and the
strategies adopted by the players may not be available, we apply a genetic algorithm to enable the players to learn other players’ behavior. The performance evaluation results show that this genetic algorithm converges to the Stackelberg equilibrium.

INTEGRATION OF WIFI INTO WiMAX NETWORKS: MAJOR RESEARCH ISSUES AND THE RELATED APPROACHES

PROTOCOL ADAPTATION AND QoS SUPPORT

Since the WiMAX and the WiFi networks have different protocol architectures and QoS support mechanisms, protocol adaptation would be required for their internetworking. For this, the protocol adaptation mechanism in [1] proposed for Universal Mobile Telecommunications System (UMTS) cellular/WiFi internetworking can be extended for WiMAX/WiFi integrated networks. For example, with a layer 2 approach, adaptation would be required in the medium access control (MAC) layer for the WiMAX BS and WiFi nodes. With a layer 3 approach, the adaptation would be performed at the IP layer, and a WiFi user would interact only with the corresponding WiFi AP/router (as in Fig. 1). This layer 3 approach is preferred for this WiMAX/WiFi integrated network, since WiFi APs/routers can fully control bandwidth allocation among the nodes. Since a WiFi AP/router is responsible for protocol adaptation up to the IP layer, modifications of WiFi user equipment and the WiMAX BS (in hardware and/or software) are not required.

QoS support would be required for real-time (e.g., video and voice) traffic in an integrated WiMAX/WiFi network. While WiMAX networks have a predefined QoS framework, WiFi networks also support QoS at the MAC layer based on the IEEE 802.11e standard. The WiMAX QoS framework supports three major service types: unsolicited granted service, polling service, and best effort service. This framework facilitates the implementation of traffic scheduling and resource management to achieve the QoS requirements. On the other hand, IEEE 802.11e supports two major traffic types: low and high-priority traffic. A QoS framework with service mapping (e.g., as in [2]) would be required for WiMAX/WiFi internetworking to support different types of traffic (e.g., constant bit rate, variable bit rate, best effort). Also, the impacts of mobility need to be considered in the QoS framework (e.g., as in [3]).

An open question related to QoS support in an integrated WiMAX/WiFi network is whether QoS should be provided on a per-flow or an aggregate basis. Although the per-flow approach can guarantee QoS for individual flows, the complexity is high. Alternatively, the aggregate approach can reduce this overhead by grouping multiple flows with similar QoS requirements together and servicing them as a single traffic class. The radio resource allocation mechanisms need to be developed accordingly. Specifically, optimal and adaptive bandwidth sharing mechanisms need to be developed to satisfy both the WiMAX and WiFi service providers.

PRICING

While the protocol adaptation and QoS issues mostly address the technical challenges in the integration of WiMAX and WiFi networks, the pricing issue relates to the control of radio resource usage from an economic point of view. The pricing model in a network affects the amount of resource allocation to subscribers and the revenue of the network service providers.

In an integrated WiMAX/WiFi network, where the WiMAX and WiFi networks are operated by different service providers, one service provider can adjust its strategies to achieve the target objective by observing the pricing offered by the other service provider as well as the demand generated from the QoS requirements in its own network. Two major approaches to pricing based on optimization formulation and game theory are discussed below.

Optimization-Based Pricing — The seminal work in [4] optimized rate allocation based on pricing in a wired network to maximize system utility. Assuming that the rate is a function of price, the optimization formulation was decomposed as network and user utility optimization. Subsequently, a dual-primal method was applied to obtain optimal pricing and rate allocation for the network and the user. A similar approach was used in [5] to develop a price-based distributed algorithm for rate adaptation in wireless networks so that the network utility (in terms of both rate and reliability performances) can be maximized. Again, the problem of network utility optimization was decomposed into two subproblems, for source and link, representing user and network entities, respectively. Since the utility was defined in terms of both rate and reliability, the prices considered in this optimization formulation were defined for both performances. In order to obtain the solution, a distributed and iterative price update algorithm was proposed. One big challenge in designing such an algorithm for an optimization-based model is to ensure stability of the algorithm and its convergence to the global optimal solution. Again, since an optimization-based formulation maximizes/minimizes the objective function which is defined for the system as a whole, the solution may not satisfy all the related entities individually.

Figure 1. An integrated WiMAX/WiFi network.
Game-Theory-Based Pricing — Game theory is one of the most popular mathematical models used to analyze the interaction among multiple entities in a wireless network. It is suitable for systems with multiple entities where each entity has its own objective; for example, a wireless network where service providers want to maximize their profit while users want to achieve their best QoS performance. In contrast to an optimization-based approach, a game-theoretic formulation aims at providing individually optimal solutions, which is more suitable for a situation where many entities interact with each other to achieve their interests.

Three major components in a game-theoretic model are the players, the strategies of the players, and the payoffs for the players. In a game any different players choose their strategies, and the payoff for a player denotes the outcome of playing the game. The objective of a game is to obtain a strategy profile (set of strategies for all players) such that all players are satisfied. This is referred to as an equilibrium, and the most common equilibrium concept used in game theory is the Nash equilibrium. This Nash equilibrium is defined as the set of strategies for all players such that no player can increase his/her payoff by choosing a different strategy, given the other players’ strategies. In addition to the Nash equilibrium, there are other solution concepts such as the max-min solution and Stackelberg equilibrium. These equilibrium concepts have different properties that could be suitable for different types of games. For example, the max-min solution is able to guarantee that the minimum payoff of each player is maximized, while the Stackelberg equilibrium ensures that payoff for one of the players (defined as the leader) is maximized.

The work in [6] used game theory to analyze pricing in a WiFi network considering two possible pricing scenarios. In the first scenario a WiFi AP sells the service to a client directly, and the players of the bandwidth sharing game are the WiFi service provider and WiFi customers. In the second scenario service is sold through a reseller, where the players are the WiFi service provider, reseller, and WiFi customers. The payoff for a customer is computed based on two different utility functions for Web browsing and file transfer applications. The durations of connections were considered in the utility functions.

The work in [7] investigated the pricing problem in a multihop wireless mesh network where the mesh nodes relay traffic to an Internet gateway. In this model intermediate routers were modeled as bandwidth resellers. The gateway (i.e., node connected to the Internet) charges the intermediate routers, and the intermediate routers charge the client nodes. First, a system model with unlimited link capacity was analyzed, and it was shown that fixed price can achieve optimal utility. Then the model was extended for a limited capacity case, and a new pricing scheme, fixed-rate noninterrupted service was proposed. In this scheme variations in the number of connections in the adjacent routers and clients were considered. An optimal price was obtained by considering the number of ongoing connections. The problem was formulated as a Markov decision process, and a policy iteration method was applied to obtain the solution.

Application of a pricing model (similar to each of those described above) to an integrated WiMAX/WiFi network would require us to consider the resource demand function from the WiFi clients. In general, if the price changes, the degree of resource requirement will vary accordingly; for example, increasing the price will decrease the demand for the resources. Also, the QoS requirements for the SSs need to be considered which have a constant demand function (and are charged using a flat rate).

For an integrated WiMAX/WiFi network, the problem of radio bandwidth management/sharing was addressed in [8]. In particular, a hierarchical bandwidth allocation was proposed based on game theory. The problem was decomposed into multiple levels, and at each level a game was formulated and solved to obtain fair resource allocation. This work was extended in [9] for integration of WiFi in multihop WiMAX networks where the WiMAX network is used as the backhaul for WiFi hotspots. However, these works ignored the pricing issue. Also, the bandwidth demand was assumed to be inelastic; thus, the QoS requirements were assumed to be independent of the price.

Pricing for Bandwidth Sharing in an Integrated WiMAX/WiFi Network

System Description

We propose a pricing model for adaptive bandwidth sharing in an integrated WiMAX/WiFi network (Fig. 1) where the WiMAX BSs and WiFi routers are operated by different service providers. In the system model under consideration, the WiMAX BSs charge the WiFi APs/routers for sharing the licensed WiMAX spectrum to provide mobile broadband Internet access to the WiFi clients. The WiMAX SSs have fixed bandwidth demand, and therefore subscribe at a flat rate to the WiMAX BS. On the other hand, the WiFi networks have elastic (i.e., time-varying) demand depending on the number of nodes and their preferences. Therefore, the WiMAX service provider charges the WiFi networks with adjustable pricing (i.e., $P_1$ and $P_2$ for WiFi routers one and two, respectively). We formulate the pricing problem as a Stackelberg game in which the profit of the WiMAX BS is maximized, and the WiFi routers are satisfied with the bandwidth sharing and pricing. The solution of this game (i.e., the Stackelberg equilibrium) can be obtained easily if the information of all service providers and customers are available.

However, in a practical system, the WiMAX BS may not know the preference of the WiFi APs/routers. Also, a WiFi router may not know the bandwidth demand functions of the WiFi nodes. Therefore, they must learn from historical data to achieve the equilibrium. For this, the proposed bandwidth sharing and pricing model uses a genetic algorithm for learning, and the knowledge thus gathered is used to choose the best strategy to achieve the desired objective.
In the system model under consideration, the service provider learns by trying several decision options. Then the result is collected and maintained in the population of a genetic algorithm. The decision of the next iteration utilizes the knowledge stored in the population, and the iterative algorithm ultimately converges to the equilibrium (as demonstrated later in this article).

**AIR INTERFACE**

We consider a single BS with multiple connections from SSs and WiFi APs/routers using the time-division multiple access/time-division duplex (TDMA/TDD) access mode based on single carrier modulation (e.g., WirelessMAN-SC air interface). We consider downlink transmission from the WiMAX BS, and the frame size is assumed to be 5 ms. The total bandwidth of operation for the WiMAX BS is 20 MHz, and for “wireless” transmission the BS uses quaternary phase shift keying (QPSK) modulation and a coding rate of 1/2. Each AP/router has a dual radio transceiver that can work using both 802.11 and 802.16 interfaces. Traffic is transmitted from the BS using the WiMAX radio interface and relayed through the WiFi AP/router using the WiFi interface to the WiFi nodes.

**REVENUE AND ELASTIC DEMAND**

The revenue of the WiMAX BS from the service provided to the SSs is a function of the corresponding QoS performance. On the other hand, the WiMAX BS charges different prices to different WiFi APs/routers depending on the bandwidth demand from WiFi clients. This type of pricing model is particularly suitable for an environment in which the SSs serve real-time traffic (e.g., those for real-time polling service [rtPS]), while the WiFi networks serve best effort traffic.

For the SSs, the queuing delay is the QoS metric, and the revenue of the WiMAX BS is expressed as

\[ R_i = \sum_{j=1}^{N_i} \left[ a_i - e_i D(\lambda_i, b_i) \right] \]

where \( a_i \) and \( e_i \) are constants (e.g., \( a_i = 1 \) and \( e_i = 1 \)), \( D(\lambda_i, b_i) \) is the queuing delay, \( \lambda_i \) is the traffic arrival rate at SS \( i \) (e.g., \( \lambda_i = 0.2 \text{ Mbps} \)), \( b_i \) is the allocated bandwidth, and \( N_i \) is the total number of SSs. Note that \( a_i \) indicates the fixed revenue, while \( e_i \) is the decreasing rate of revenue due to the queuing delay at the corresponding SS. When \( a_i \) is large, the SS earns higher revenue, while with larger \( e_i \), the cost due to delay becomes higher and the revenue becomes smaller.

The bandwidth demand by a WiFi node depends on the price charged by the WiFi AP/router. We assume a linear demand function expressed as follows: \( b_j(P_k^{(r)}) = c_j - d_j P_k^{(r)} \), where \( b_j(P_k^{(r)}) \) is the bandwidth demand of node \( j \) served by WiFi AP/router \( k \) for given price \( P_k^{(r)} \), and \( c_j \) and \( d_j \) are constants (e.g., \( c_j = 2.0 \) and \( d_j = 0.4 \)), and \( P_k^{(r)} \) is the price charged at WiFi AP/router \( k \). Note that \( c_j \) denotes the fixed bandwidth demand (i.e., when the price is zero), and \( d_j \) denotes the elasticity (i.e., slope) of the demand function. If \( c_j \) is large, the bandwidth demand is high. If \( d_j \) is large, the elasticity of the demand increases (i.e., the WiFi AP/router is more sensitive to the increase in price).

The revenue of the WiFi network \( k \) is obtained from

\[ R_k = \sum_{j=1}^{N_f} \left[ F_j(P_k^{(r)} - F_k^{(r)}) \right] \]

and the cost is calculated from

\[ C_k = P_k^{(b)} \sum_{j=1}^{N_f} b_j(P_k^{(r)}) + F_k^{(r)} \]

where \( P_k^{(b)} \) is the price charged by the WiMAX BS to the WiFi AP/router \( k \), \( N_f \) is the number of WiFi nodes served by router \( k \), and \( F_k^{(r)} \) denotes a fixed cost for a WiFi router. Note that the profit depends largely on the demand function, which we may not be able to obtain analytically. However, an empirical method as in [10] can be used.

**STACKELBERG GAME AND PROFIT MAXIMIZATION**

In economics, the Stackelberg game is used to analyze competition in an oligopoly market [11] (i.e., a market with a few suppliers). In such a market there is a leader player who is able to commit a strategy before other follower players. The equilibrium of this formulation can be obtained by backward induction. For the case of oligopoly competition in quantity, the leader considers the best response of the follower. Then the leader uses this best response information to choose the optimal supply quantity to gain the highest profit.

We apply this Stackelberg game structure to obtain the equilibrium of bandwidth sharing and pricing between WiMAX and WiFi service providers. With an assumption that the WiMAX and WiFi service providers are rational to maximize their profits, the game can be described as follows:

- **The players**: The WiMAX BS (i.e., leader) and WiFi APs/routers (i.e., followers) are the players of this game.
- **The strategies**: For the WiMAX BS, the strategy is the price \( P_k^{(b)} \) charged to the WiFi APs, and for a WiFi AP, the strategy is the required bandwidth \( b_j^{(r)} = \sum_{j=1}^{N_f} b_j(P_k^{(r)}) \).
- **The payoffs**: For both the WiMAX BS and WiFi APs/routers, the payoffs are the corresponding profits.

We first consider the payoff for a WiFi AP/router. Given the price charged by the WiMAX BS, \( P_k^{(b)} \), the profit of AP \( k \) is

\[ \pi_k = R_k - C_k = \sum_{j=1}^{N_f} b_j(P_k^{(r)}) \left( c_j - d_j P_k^{(r)} \right) - P_k^{(b)} \sum_{j=1}^{N_f} \left( c_j - d_j P_k^{(r)} \right) - P_k^{(r)} \]

Therefore, the optimal price charged to a WiFi node (i.e., \( P_k^{(r)} \)) can be obtained by differentiating the profit function and then setting it to zero. Then, given price \( P_k^{(r)} \), the bandwidth demand for all WiFi nodes in hotspot \( k \) can be obtained. Based on the best response of the WiFi AP/router, the WiMAX BS can adjust the
price $P_{k}^{(br)}$ charged to router $k$ to achieve the highest payoff. The payoff (i.e., profit) of the WiMAX BS can be defined as follows:

$$\pi = P^{(s)} + \sum_{k=1}^{N} p^{(r)}_{k} = \sum_{i=1}^{N_i} \left[ a_i - c_i(D_i(b_i^{(r)})) \right] + \sum_{k=1}^{N} p^{(br)}_{k} D_{k},$$

where $N$, is the total number of WiFi APs/routers.

The Stackelberg equilibrium is defined as the strategy profile that maximizes the leader's payoff while the follower plays his/her best response [11]. We consider this equilibrium as the solution of the bandwidth sharing and pricing game to ensure that the profit of the WiMAX BS, which is the major player of this game, is maximized.

Where all information on demand function is completely known, the equilibrium can be achieved easily by differentiating the profit function of the WiMAX BS and solving it for the price $P_{k}^{(br)}$. However, in a practical system this information may not be available (e.g., WiFi service providers do not want to reveal customer preferences to outside network entities). Therefore, we use a genetic algorithm to estimate and adapt the strategies of WiFi APs/routers (i.e., followers) to achieve the best response and the strategy of WiMAX BS (i.e., leader) to reach the equilibrium.

**GENETIC ALGORITHM AND LEARNING PROCESS**

In order to learn users’ preference (i.e., bandwidth demand), we apply a genetic algorithm [12]. The configuration of the algorithm is shown in Fig. 2. A genetic algorithm is employed at the WiMAX BS and WiFi AP/routers to gain knowledge of bandwidth demand and adjust the price. With backward induction beginning at the WiFi router, the game is solved. That is, the population at a WiFi AP/router evolves by the genetic algorithm to achieve the highest profit based on the demand of all WiFi nodes and also on the given price charged by the WiMAX BS. In this case each population maintains the price charged to the WiFi nodes. Then the WiFi AP/router informs the WiFi nodes of this price, and each WiFi node responds with the bandwidth demand (which is obtained based on a demand-price function). The WiFi AP/router updates the aggregated demand of all nodes and feeds this information to the genetic algorithm to update the information stored in the population. This process iterates until the profit for the WiFi AP/router is maximized. Similarly, the WiMAX BS broadcasts the price for bandwidth to be charged to the WiFi AP/router. The genetic algorithm at the BS causes evolution to the population based on the bandwidth demand that is the best response from each WiFi router. This process iterates until the equilibrium (i.e., maximum profit) is reached.

**NUMERICAL RESULTS**

First, the profit of the WiMAX BS is obtained for the case when the information on demand function is completely known (Fig. 3). Here, the WiFi routers serve four and six WiFi nodes, and the number of SSs is 10. The profit changes due to the different prices charged to the WiFi APs/routers, and there is also a point where the profit of the WiMAX BS is maximized. This point is the equilibrium of this Stackelberg game formulation. As is evident from Fig. 3, this profit, which is a function of price, is unimodal. Therefore, with complete network information, the equilibrium can be achieved easily. However, in a practical system this assumption may not be valid, and a learning or evolutionary algorithm is required to reach this equilibrium through interaction between the leader and followers in the game.

Figures 4a and 4b show the optimal price for the WiMAX BS to charge the WiFi routers and the bandwidth to share with the WiFi routers. We consider the case when the first and second WiFi APs/routers serve four and six WiFi nodes, respectively. All the SSs have the same traffic arrival rate. Interestingly, even though the prices charged to the first and second WiFi APs/routers are formulated as different strategies in the
game, at the equilibrium they are always equal. This implies that the WiMAX BS should charge the same price to the WiFi routers even though their bandwidth demands may be different. Also, as expected, when the traffic arrival rate increases, the WiMAX BS needs to increase the price charged to the WiFi routers to compensate for the loss in revenue due to the degraded QoS performance (i.e., higher delay) for the SSs. Consequently, the bandwidth demand of both WiFi APs/routers decreases. At the same price, bandwidth demand of the first WiFi router becomes smaller than that of the second router due to the smaller number of WiFi nodes.

Then we vary the number of WiFi nodes served by router two, and observe the price and the amount of bandwidth shared at the equilibrium (Fig. 5). We set the number of SSs to 16, and the traffic arrival rate is assumed to be 0.5 Mb/s. As expected, when the number of nodes increases, the bandwidth demand from the WiMAX BS increases. Consequently, the price charged to the WiFi APs/routers increases. We observe that the bandwidth allocated to WiFi router two increases significantly, while that to WiFi router one slightly decreases. This is due to the fact that the WiMAX BS can take some bandwidth from the SSs (instead of taking bandwidth from other WiFi routers) with only slight degradation in their delay performances.

**CONCLUSIONS**

In this article we have presented an integrated WiMAX/WiFi network architecture for mobile hotspot services. Such a network would be useful, for example, to provide wireless connectivity for intelligent transportation system (ITS) applications. Game theory has been used to analyze and obtain the optimal pricing for bandwidth sharing between a WiMAX BS and WiFi APs/routers, taking into account the bandwidth demand of the WiFi users. A genetic algorithm has been used to iteratively obtain the solution of this game when complete bandwidth demand information is not available. This proposed bandwidth sharing and pricing scheme will be useful for both WiMAX and WiFi service providers to adopt efficient business strategies for integrated WiMAX/WiFi networks.

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**Figure 4.** a) Price and b) bandwidth sharing at the equilibrium under different traffic loads at the subscriber stations.

**Figure 5.** Price and bandwidth sharing at the equilibrium under different numbers of WiFi nodes served by WiFi router two.
REFERENCES


BIOGRAPHIES

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