Market Models and Pricing Mechanisms in a Multihop Wireless Hotspot Network

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***Abstract*— Multihop wireless hotspot network [1]–[4] has been recently proposed to extend the coverage area of a base station. However, with selfish nodes in the network, multihop packet forwarding cannot take place without an incentive mechanism. In this paper, we adopt the "pay for service" incentive model. i.e., clients pay the relaying nodes for their packet forwarding service. Our focus in this paper is to determine a "fair" pricing for packet forwarding. To this end, we model the system as a *market* where the pricing for packet forwarding is determined by demand and supply. Depending on the network communication scenario, the market models are different. We classify the network into four different scenarios and propose different pricing mechanisms for them. Our simulation results show that the pricing mechanisms are able to guide the market into an equilibrium state quickly. We also show that maintaining communication among the relaying nodes is important to achieve a stable market pricing.**

***Index Terms*— Multihop wireless hotspot network, incentive engineering, network pricing, hill-climbing, marginal cost, VCG mechanism.**

I. INTRODUCTION

We consider a multihop hotspot network as illustrated in Figure 1. In this architecture, a mobile client may not be able to reach the base station (BS) via single-hop direct communication. Instead, the client must rely on another node who is closer to the BS to forward its packets. Such nodes are called the relaying nodes (RN). This is the *multihop wireless hotspot network* proposed in recent literatures [1]–[4]. A similar multihop architecture for cellular network has also been proposed recently [5]–[9].

Compared to the traditional single-hop hotspot network where every node communicates directly to the BS, a multihop hotspot network offers a few advantages. First, it extends the coverage of the BS to a larger area, which is helpful especially when installing additional BS is not possible due to real property restrictions. Second, it may increase the throughput of a client who receives very bad signal from the BS, while a nearby relaying node

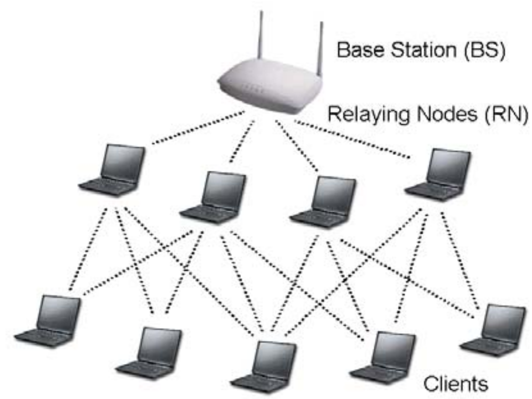

Fig. 1. Example of a Multihop Wireless Hotspot Network

has much better wireless signal quality. This situation is possible considering the irregular signal propagation property in a physical environment with partitions and obstacles. Finally, by multihop forwarding, a client does not need to have subscription to the BS to use its service. This is helpful when a client roams outside its own hotspot ISP's service area.

In this paper, we focus on providing *incentive* for packet forwarding in a two-hop hotspot network. [1] Since packet forwarding consumes a RN's resources such as bandwidth and energy, a *selfish* RN would not be willing to forward other's packets without an incentive mechanism. In this paper, we adopt the "pay for service" incentive model, i.e., clients pays the RNs to forward their packets. In human society, monetary rewards are often given for providing service. Here, packet forwarding can be considered as RN's "service" to the clients, considering the fact that the RNs are owned and controlled by human users.

Our focus in this paper is to determine a "fair" pricing for the packet forwarding service in this network. To this end, we model the system as a *market* where the pricing for packet forwarding is determined by demand and supply. The RNs compete for clients' traffic; clients can choose a RN who can offer a better price, similar to

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[1] We choose two-hop instead of the general N-hop architecture due to its simplicity and its common and practical use.

in a multiple-buyer multiple-seller market. Its difference with the conventional market is that the communication scenarios in this network can be very complex, leading to different market structures.

The market structure in this network depends on the number of RNs, the communication among the RNs, and the reachability of the clients to the RNs. For example, if there is only one single RN in the network, the RN becomes a *monopolist* who has unique pricing power. Therefore, the RN can *probe* the client(s) with different prices to maximize its profit. However, if there are multiple RNs, such pricing power is rather limited. Instead, the RNs have to compete with each other by undercutting each other's price. Therefore, we classify the network into four different scenarios and propose different pricing mechanisms for them (details in Section III). In particular, we introduce a hill-climbing algorithm for a monopoly market (i.e. single RN in the network), and a second lowest marginal cost pricing mechanism for a market with multiple RNs and perfect reachability. We further extend these basic network scenarios to cover a situation where a client can only reach a subset of the relaying nodes, and another situation where the relaying nodes do not have communication among them. A summary of the scenarios and their solutions are given in Table I (Section III).

Our contributions in this paper are as follows: 1) we classify the multihop hotspot network into different communication scenarios and propose different market pricing mechanisms for them; 2) we introduce a VCG-like second lowest marginal cost mechanism which guarantees truthful reporting of costs; and 3) we demonstrate the importance of keeping communication among the RNs for a stable market.

The rest of the paper is organized as follows. In Section II, we present backgrounds and concepts of a market in micro-economics. In Section III we discuss in detail the network scenarios and their market structures. This is followed by evaluations of our solutions in Section IV. We discuss the related work in Section V and conclude the paper in Section VI.

II. Background and Concepts

In this section we present backgrounds and some related concepts of a market in micro-economics.

A. Incentive for Packet Forwarding in MANET

Creating incentive for packet forwarding is an important problem in a multi-hop ad hoc network (MANET). There are two general approaches: game theory based approach [10]–[16] and credit (or micro-payment) based approach [17]–[20]. In game theory approach, a *packet forwarding game* is designed and played by all the nodes in the network. In early studies [10]–[13], each node is ranked with a *reputation* based on its packet forwarding behavior observed by other nodes in the same neighborhood. A node with bad reputation is then refused service by other nodes, and hence isolated from the network. If the cost of a bad reputation is prohibitively high, all the nodes will choose to cooperate. Recent studies [14]–[16] examine the forwarding dependency in the packet forwarding game. For example, in [14] the concept of a *dependency graph* is introduced to represent the forwarding dependency of a node to another. When there are mutual dependencies between two nodes, the packet forwarding game can be modeled as a repeated Prisoner's Dilemma game, where a simple "tick-for-tack" strategy can be implemented to encourage mutual cooperation [14]–[16]. The dependency requirement means that, a node's cooperative behavior can be enforced *only* when its non-cooperative behavior can be "punished" by the nodes that it has previously refused to serve for. If there is no such mutual dependency, cooperation cannot take place.

In our multihop hotspot network (Fig. 1), forwarding dependency clearly does not exist since packet forwarding is always one-way, i.e., from the clients to the base station. Therefore, the game theory approach cannot be used in this network. Therefore, we adopt the credit (micro-payment) approach where the clients pay the RNs for their forwarding service. One important problem is how to determine a "fair" pricing for packet forwarding. To this end, we model the forwarding service as a market where the market pricing is determined by the demand of the clients ("buyers") and the competition between the RNs ("sellers").

B. Demand Curve

The demand of a product in a market is related to its price. When the price is low, the demand is high. This relation can be captured by a function called *demand curve*. Fig. 2 is an example of a demand curve called the *modified iso-elastic* demand curve. It has the following mathematical definition:

$$P = \frac{1}{W + Q} \tag{1}$$

where P is the price, Q is the demanded quantity, and W is the reciprocal of the maximum price obtainable (or upper-bound of price) when production tends to go to zero. This demand curve has been used in economic research and is considered to be quite realistic [21].

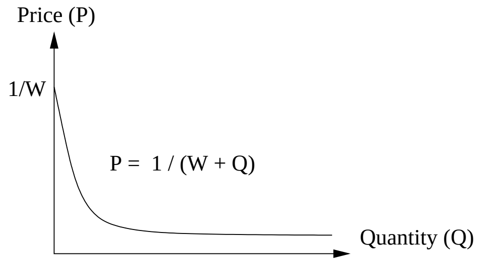

Fig. 2. A modified iso-elastic demand curve.

In our market, the price is the reward for forwarding one unit of traffic (i.e. $/Byte). The demand is measured by the amount of traffic a client is requesting (i.e. Bytes). When the price is low, the client demands more traffic. Note that the demand curve is *private* to the client, and the client is not willing to reveal this curve to the RNs.

C. Marginal Cost

Packet forwarding incurs a cost to the RN. *Marginal cost* (MC) is defined as the cost of offering the next unit of service to the clients. This may include hotspot subscription cost, computer equipment, etc. This cost may also include a variable part depending on the level of battery power left on the mobile device. For example, assume a user's monthly hotspot subscription fee is $50 and the monthly equipment cost is $50. The traffic that can be forwarded in a month can be estimated as: 30 days * 5 hours * 3600 seconds * 100 Kbps. Then, the fixed part of MC of forwarding one byte of data is: $1.5 * 10^{-8}$ ($/Byte). At the same time, the variable part of MC may depend on the power left on the device. For example, when power is below 50%, the user may attach $1 cost to the depletion of power. The 50% power can sustain 1 hour of operation during which 3600 seconds * 100 Kbps data can be sent. Then, the variable part of the MC when power is low can be estimated as: $2.2 * 10^{-8}$ ($/Byte), and the total MC becomes: $3.7 * 10^{-8}$ ($/Byte). If the power is even lower (e.g. 10%), the traffic that can be forwarded is smaller and hence the MC for each packet is higher. Since the change of battery is gradual, we expect the MC of each RN to be relatively stable.

Clearly, each RN has its own valuation of resources. Therefore, their MCs are likely to be different. In our market model, each RN is free to determine its own MC for packet forwarding.

D. Monopoly and its Profit Maximization

A *monopoly* is defined as a market in which there is only one seller. This corresponds to the situation where there is only one RN in the network. Since the monopolist has unique pricing power in the market, it will try to find an optimal price to maximize its profit.

The monopolist can derive its optimal price as follows. Assume the marginal cost is c and the market's demand curve [2] is defined in Eq. 1. The monopolist's *profit function* can be computed as:

$$Profit(P) = (P - c)Q = 1 - PW - \frac{c}{P} + cW \quad (2)$$

If the demand curve is known, the monopolist can compute an optimal price $\mathcal{P}$ based on the profit function. [3] However, since the demand curve of the market is *not* known by the RN, a closed form computation of the optimal price is not possible. Just "ask" the clients would not be very helpful since the clients have incentive to lie about the demand curve to gain advantage.

In our model, we let the RN *probe* the client(s) to determine the optimal price, using a specially designed *hill-climbing* algorithm which is quick and accurate (details in Section III-B).

E. Price Undercutting and Second Lowest MC

When there are multiple RNs in the network, they may engage in a "price war" to undercut each other. To illustrate this, let's consider a simple example with three RNs with marginal costs: $c_1 < c_2 < c_3$. Assume that initially the price is higher than c_3, and it is gradually reduced due to price competition. When the price is reduced to $c_3 - \epsilon$, the third RN quits the market because it has negative profit at this price. Likewise, the second RN quits the market when the price is reduced to $c_2 - \epsilon$. At this point, since the first RN has nobody to compete against, it does not have to reduce its price any further (i.e. below $c_2 - \epsilon$). Therefore, the final result of this competition is that, the RN with the *lowest* MC wins the competition, with a market price equal to the *second lowest* MC. In the example above, the first RN wins the competition with a price equal to c_2 (the second lowest MC).

To accelerate this competition, we let the RNs *announce* their MCs to the market, and set the final price at the second lowest MC without going through the lengthy price undercutting process. One problem with this pricing mechanism is that the RNs may "cheat" by announcing a false marginal cost. Based on a similar proof of the Vickrey auction, we show that the second lowest MC pricing mechanism is able to encourage the RNs to report their marginal costs *truthfully* (details in Section III-C).

[2] The market's demand curve is determined by the aggregate of the clients' demands under different prices.

[3] A simple calculation gives $\mathcal{P} = \sqrt{\frac{c}{W}}$.

III. Network Scenarios and their Pricing Solutions

In this section we describe in detail the network scenarios and their market structures. We then propose different pricing solutions for these markets.

A. Network Scenarios and Market Structures

We classify the network into four different scenarios (shown in Table I). Their differences are: 1) the number of RNs in the network; 2) whether communication exists among the RNs; and 3) whether the clients can reach all RNs or only a subset of them. We relax these conditions one by one from the first scenario (S1) to the last one (S4).

Each of these scenarios leads to a different market structure. S1 depicts a simple monopoly market where the RN probes the market to maximize its profit. S2 is a simple competitive market where a client can choose service from every RN, and the RNs are aware of each other's price announcements. As mentioned earlier, we adopt the VCG-like second lowest marginal cost pricing mechanism to avoid lengthy price undercutting and to encourage truthful reporting of marginal costs. In S3, since a client can only reach a subset of the RNs, we extend the second lowest marginal cost mechanism to cover only those RNs a client can reach, and introduce a mechanism to prevent false claims of reachability by the clients. In S4, since the RNs now do not have information about each other's costs, a concurrent probing method is used by each RN to determine its optimal price. We investigate the price in equilibrium and show that in order to have a stable market, maintaining communication among the RNs is very important.

B. Scenario 1

In this scenario, there is only one single RN (monopolist) who probes the client(s) to maximize its profit. Here we propose a quick converging *hill-climbing* algorithm for this purpose.

The goal of the hill-climbing algorithm is to search an optimal price $\mathcal{P}$ such that the RN's profit is maximized. If the profit function $Profit(\mathcal{P})$ as defined in Eq. 2 is a correct representation of the market, RN's profit should increase monotonically to its maximum and decreases monotonically after that, i.e., it has a single "peak". [4] Although it is almost impossible to determine the exact shape of the demand curve and profit function, we can reasonably assume that the profit function of the RN has a single peak. To this end, our hill-climbing algorithm is a general search algorithm for this type of function.

Our algorithm consists of two stages. The first stage performs a coarse but quick probing to locate a price region where $\mathcal{P}$ should belong to. The RN starts from a probing price equal to its marginal cost, and the incremental step size is always *doubled* each time to quickly encompass the optimal price. The first stage produces a relatively large target price region that includes the optimal price. In the second stage, the RN conducts a *binary* search within the target price region from the first stage to quickly narrow down the price region, by comparing the mid-point of the region with the two end-points of the region. The algorithm stops when the target price region is smaller than a pre-set accuracy threshold. Details of the algorithm and an illustrative example are given in Appendix I, which shows the fast probing (first stage) and quick converging (second stage) properties of our algorithm.

[4]This can be proved by the first-order derivative of the profit function: $Profit'(P) = \frac{c}{P^2} - W$, which shows that its sign switches only once when $P = c \to \infty$.

C. Scenario 2

In this scenario, there are multiple RNs in the network and they are aware of each other's price announcements. This is possible by broadcasting the announcement messages, or if that is not reliable enough, by BS's help to relay those messages. By definition, every RN can communicate with the BS.

As mentioned earlier in Section II-E, in this market the RNs engage in a price war to undercut each other's price. The RN with the lowest MC *wins* the competition. The charging price is set at the price of the second lowest MC. To accelerate this competition, we let the RNs announce their MCs to the market, and the final market price is set at the second lowest MC.

This pricing mechanism is similar in principle to the seal-bid second-price Vickrey auction [22], where the seller collects bids from the buyers, and sells the good to the highest bidder with a price equal to the *second* highest bid. In this auction, the optimal strategy for each bidder is to bid her *true valuation* for the good. Vickrey auction is closely related to the Clark-Groove mechanism [23], [24] in allocating public goods. Together they are often known as the "VCG mechanism", which has influenced the field of mechanism design in distributed agents (e.g. [25]).

The second lowest MC pricing mechanism can be considered as a "reversed" auction where the RNs ("sellers") compete for the clients ("buyers"). Similar to Vickrey auction, we show that the RNs have incentive to report their MCs *truthfully* under this pricing mechanism.

TABLE I
NETWORK SCENARIOS AND THEIR MARKET STRUCTURES

Scenario	No. of RN	RN Comm.	Reachability	Outline of Solution
S1	Single	Yes	All RNs	RN probes the market for optimal price to maximize its profit.
S2	Multiple	Yes	All RNs	Price is determined by the second lowest MC of all RNs.
S3	Multiple	Yes	Subset	Price is determined by the second lowest MC of the RNs a client can reach.
S4	Multiple	No	Subset	Concurrent price probing by all the RNs (second lowest MC in equilibrium).

Property 1 (Truthful Reporting of Marginal Cost): Under the second lowest marginal cost pricing mechanism, each relaying node (RN) has incentive to report its true marginal cost to the market. [5]

Proof: We denote a RN's true MC as c, and its reported value as c'. The *lowest* reported MC of all the other RNs is c'_l. Now let's focus on the RN's reporting strategy and its profit. There are two possibilities that the RN can deviate from truthful reporting: *under-reporting* and *over-reporting*.

Case of under-reporting: the reported MC is lower than the true MC (i.e. $c' < c$). Now, consider the following three possibilities: 1) If $c < c'_l$, the RN wins the competition, and the outcome is *exactly* the same as if the RN had reported the true MC, because the price is determined by the second lowest MC which is c'_l. 2) If $c' < c'_l < c$, although the RN wins the competition, it has *negative* profit because the price c'_l is *lower* than its true marginal cost. This is not a desirable outcome. 3) If $c'_l < c'$, the RN lost the competition, which is exactly the same outcome as if it had reported the true MC. Therefore, the RN has no incentive to under-report its MC.

Case of over-reporting: the reported MC is higher than the true MC (i.e. $c < c'$). Again consider the following three possibilities: 1) If $c' < c'_l$, the RN wins the competition, and the outcome is exactly the same as if the RN had reported the true MC, because the price is determined by c'_l. 2) If $c < c'_l < c'$, the RN loses the competition and hence its profit is zero. It could have won the competition by reporting its true MC and still gain some positive profit since $c'_l - c > 0$. This is clearly not a desirable outcome. 3) If $c'_l < c$, the RN lost the competition, which is exactly the same outcome as if it had reported the true MC. Therefore, the RN has no incentive to over-report its MC.

In summary, a RN gains more profit by reporting its MC truthfully, no matter what the other RNs do. Therefore, the RNs have incentive to report their true MCs under this pricing mechanism. ■

[5]Note that we assume the RNs do not collude.

Under this market model, only the two RNs with the lowest and the second lowest costs are needed to maintain the price. As a result, other higher cost RNs will refrain from announcing their costs in order to reduce signaling overheads. However, they should still keep monitoring the market to see whether their own costs will be needed in the future, possibly due to the departure of the current lowest cost RNs. When a RN detects that it is the *only* RN in the network, it will switch to monopoly mode (Scenario 1) and start to probe the client(s) to maximize its profit.

D. Scenario 3

Scenario 3 differs from Scenario 2 in that each client can only reach a subset of the RNs, i.e., a client may not be able to use the service of the lowest cost RN. As a result, the pricing mechanism in Scenario 2 does not apply to this scenario. Note that the RNs are still aware of each other's price announcements.

We extend the second lowest MC pricing mechanism to cover the subset reachability scenario here. That is, the second lowest MC pricing mechanism is considered only within the subset of RNs that the client can *actually* reach. For example, if there are five RNs in the network but a client can only reach three of them, the client has only three choices. It should go to the lowest cost RN it can reach, but pays the second lowest cost in the subset. Intuitively, this is because *if* the lowest cost RN refuses to serve the client, the client has to go to the second lowest cost RN. Therefore, the lowest cost RN has the "bargaining power" up to the second lowest cost, and therefore should be able to ask for that price.

However, there are two outstanding problems in this pricing mechanism. The first problem is that the client should be prevented from making *false* claims of its reachability to the RNs. For example, if a client can reach a certain RN but later lost contact with it, the client should not be allowed to make the claim any more. There are a number of possible solutions to this problem, such as using time-stamps or sequence numbers with digital signatures. We choose to use a very simple technique. That is, when a RN announces its MC to the network, it attaches a *random number* with the announcement. As a result, if a client has lost contact with a RN, the RN's old announcements will become obsolete since the latest announcement has a different random number. Since the RNs can hear from each other's announcements, they are aware of the latest number. Therefore, a client cannot make false claims about its reachability to the RNs. [6]

Second, what if a client can only reach a single RN? In our earlier scenarios (S1 and S2), we switch between market probing (for S1) and second lowest MC pricing (for S2) mechanisms, depending on the number of RNs in the network. Here we must adopt these two pricing mechanisms simultaneously with regard to different clients. If a client can only reach a single RN, the RN has monopolist power over the client and it can resort to price probing for that client. [7] As we have mentioned earlier, the client cannot lie about the set of RNs it can reach.

E. Scenario 4

In this scenario, we relax the condition that the RNs have communication among them, i.e., they are not aware of each other's price announcements. Without further information about the market, each RN has to probe the market individually to determine its optimal pricing, similar to the hill-climbing method used in Scenario 1. However, it is not clear whether *concurrent* probing of the market is able to lead to an equilibrium price.

To understand the dynamics of concurrent probing, consider the competition between two RNs. The first RN has cost c_1 and the second has cost c_2, with $c_1 > c_2$. To probe the market, each RN can use a price between its MC and infinity. Since $c_1 > c_2$, there is always a chance that the second RN can undercut the first RN's price. Then the first RN will eventually lower its price to c_1, but cannot go lower. When the second RN uses a price between c_2 and c_1, it gains the whole market with positive profit. But if it ever tries to raise its price higher than c_1, it will lose the market and has to lower its price again. In other words, c_1 serves as the upper-bound for the second RN's probing price. Ideally, the second RN should set its price at $c_1 - \epsilon$. Using a fast and accurate hill-climbing algorithm, the second RN should arrive at an optimal price close to this value. Therefore, the net outcome is that the market price is close to the second lowest MC in equilibrium, which is similar to the pricing mechanisms in S2 and S3. However, unlike S2 and S3, this "correct" price has to be reached in a probing process.

The analysis above underscores the importance of keeping communication among the RNs. It helps the market reach equilibrium *instantly* and keeps the market price stable, which translates into higher profit for the winning RN. Therefore, the BS should be *persuaded* to act as intermediate for the RNs, possibly by using a reward or profit-sharing mechanism.

[6] If two nodes collude with each other to share the announcements, it is still possible that a node can make false reachability claims. A more sophisticated technique has to be designed to prevent such collusion problem.

[7] Note that here the price probing is targeted at that client only, by using unicast price announcements.

IV. Simulations

In this section we conduct ns-2 simulations to evaluate the different pricing mechanisms in a two-hop 802.11 wireless hotspot network. There are three types of nodes in our simulation: base station (BS), relaying nodes (RN), and clients. For simplicity, we use experiment $(1, m, n)$ to denote a simulated network scenario where there are one BS, m RNs, and n clients. The clients try to send constant bit rate (CBR) traffic to the BS via the RNs. The RNs broadcast their pricing announcements to the clients.

A. Price Probing by a Single RN

Price probing by a single RN via hill-climbing is the pricing mechanism for Scenario 1 in Section III-B. Here we evaluate the accuracy and convergence of the algorithm by using two experiments: (1,1,1) and (1,1,5). We use 0.001 as the accuracy threshold for the algorithm.

Experiment (1,1,1) is the simplest case with only one client. The RN and the client's parameters are shown in Table II. The probing price of the RN is shown in Figure 3. The figure clearly shows the two stages of hill-climbing: fast probing in the first stage and quick convergence in the second stage, which is similar to Figure 11 in Appendix I. To implement hill-climbing in a realistic scenario with network traffic, RN has to measure the traffic for a certain period of time to calculate its profit reliably. In our simulations, the time interval between two price announcements is 15-30 seconds. The final probing price after 34 climbing steps is 3.1614, which is very close to the theoretic optimal price of 3.1623.

TABLE II
Simulation Parameters in Experiment (1,1,1)

Cost of the RN	0.08
W of the client	0.008

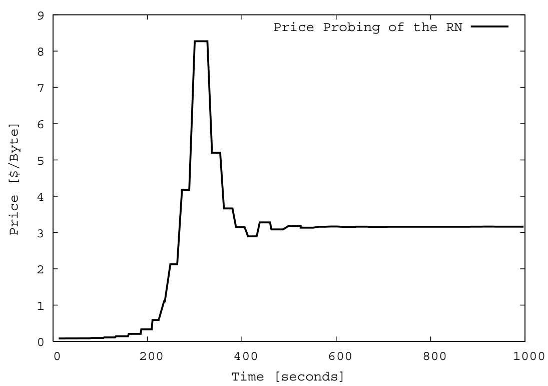

Fig. 3. RN's hill-climbing probing price in Experiment (1,1,1).

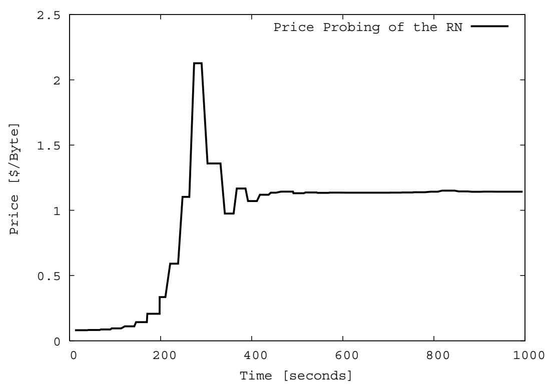

Fig. 4. RN's hill-climbing probing price in Experiment (1,1,5).

Experiment (1,1,5) is to further evaluate the accuracy and convergence of hill-climbing with multiple clients. The simulation parameters are shown in Table III. The RN's probing price is shown in Figure 4. The final price after 32 climbing steps is 1.1425, which is sufficiently close to the theoretical optimal price of 1.1359. [8]

TABLE III
SIMULATION PARAMETERS IN EXPERIMENT (1,1,5)

Cost of the RN	0.08
W of client 1-5	0.01, 0.02, 0.04, 0.08, 0.16

The hill-climbing process in the two experiments above takes about 5-7 minutes. This can be improved by one of the following techniques: 1) start from a price higher than the MC; 2) use a larger initial step size; and 3) shorten the probing interval. However, due to the probing process, hill-climbing is best suited for a more static network environment with a fixed set of clients.

[8]The theoretical optimal price for N clients can be derived as: $\mathcal{P} = \sqrt{\frac{cN}{\sum_{i=1}^{N} W_i}}$ where c is the cost of the RN, and W_i (i = 1 to N) correspond to the demand curves of the clients.

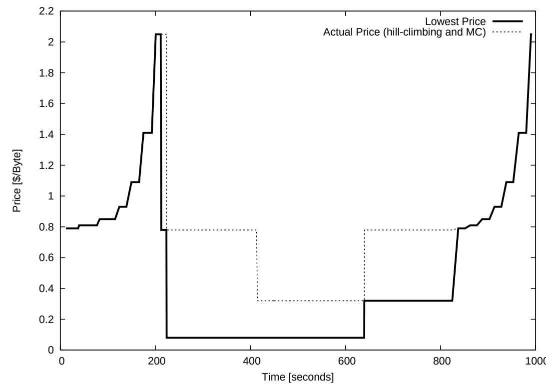

Fig. 5. The pricing curves of the RNs in Experiment (1,3,1).

B. Second Lowest Marginal Cost Pricing Mechanism

Second lowest marginal cost is the pricing mechanism for Scenario 2 in Section III-C. We will show an experiment with (1,3,1), i.e., there are three RNs competing for a client and they are aware of each other's price announcements. The simulation parameters are shown in Table IV.

TABLE IV
SIMULATION PARAMETERS IN EXPERIMENT (1,3,1)

Cost of RN 1-3	0.08, 0.32, 0.78
W of the client	0.008

The RNs arrive with staggered times: 1) during time 0s to 220s, only RN_3 is present in the network so that it resorts to hill-climbing mechanism; 2) during time 220s to 410s, RN_1 joins the network and they switch to the second lowest MC pricing mechanism where RN_1 wins the competition at the MC of RN_3; 3) during time 410s to 640s, RN_2 joins the network so that three RNs compete for the market where RN_1 wins at the MC of RN_2; 4) during time 640s to 830s, RN_1 leaves the network so that only RN_2 and RN_3 compete with each other, where RN_2 wins at the MC of RN_3; 5) during time 830s to 1000s, RN_2 leaves the network so that $RN3$ resumes its hill-climbing mechanism. The pricing curves are shown in Figure 5. Since the market price can be determined immediately using the second lowest MC mechanism, it is suitable for a dynamic network with high mobility.

The pricing mechanism for Scenario 3 in Section III-D is similar to Scenario 2 and is omitted for brevity.

C. Concurrent Price Probing by Multiple RNs

Concurrent price probing is adopted when the RNs are not aware of each other's price announcements, which

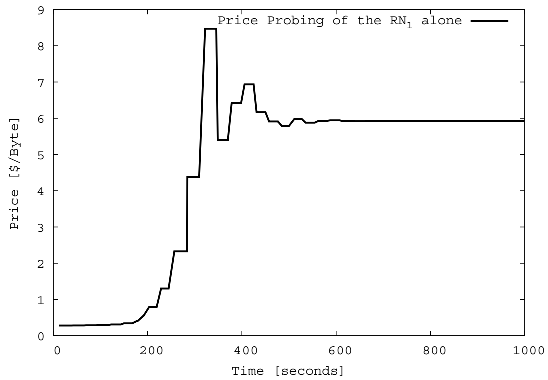

Fig. 6. Price probing if RN_1 runs alone in Experiment (1,2,1).

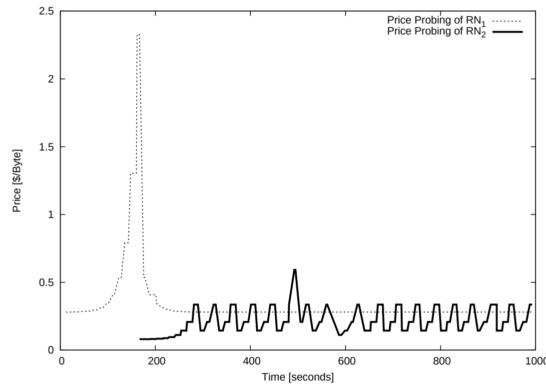

Fig. 7. Concurrent price probing in Experiment (1,2,1).

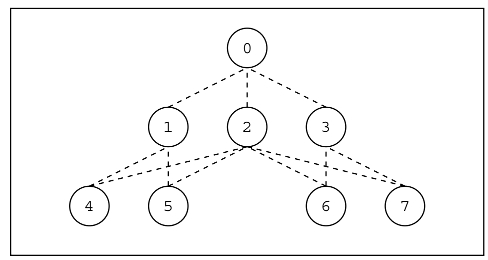

Fig. 8. Topology of experiment (1,3,4)

corresponds to Scenario 4 in Section III-E. We will show two experiments: (1,2,1) and (1,3,4).

Experiment (1,2,1) has a simple topology where there are two RNs compete with each other for a single client. The parameters are shown in Table V. The two RNs start with staggered times: RN_1 runs first (when it is a single RN in the network), and RN_2 joins later which disrupts RN_1's probing. After that, they probe concurrently. As a comparison, we show in Figure 6 RN_1's probing price if it runs alone, which gives a probing price of 5.9233 (theoretical optimal is 5.9161). When the two RNs probe concurrently, their prices are shown in Figure 7. Before RN_2 joins at time 170s, RN_1 probes alone which jumps the price really high. After RN_2 joins, since it has a lower MC, its initial probing price is lower, which lets it win over the client. At this point, RN_1 drops its price to approximately its MC, however, it still cannot attract the client. At a certain point, for example at time 290s when RN_2 reaches RN_1's MC, RN_2 cannot continue to climb higher because that would allow RN_1 to regain the market. Then RN_2 starts to cut its price, and this competition starts over in cycles at equilibrium. The overall effect is that RN_2 has to keep a price lower than RN_1's MC (which is the second lowest MC), but it is trying to get to that price as close as possible.

TABLE V
SIMULATION PARAMETERS IN EXPERIMENT (1,2,1)

Cost of RN 1-2	0.28, 0.08
W of the client	0.008

Experiment (1,3,4) investigates a more complicated case where each client can only reach a subset of the RNs. The topology is shown in Figure 8: client 4 and 5 can reach RN_1 and RN_2; client 6 and 7 can reach RN_2 and RN_3. The simulation parameters are shown in Table VI. The concurrent probing of the three RNs is shown in Figure 9. The figure shows that when RN_2 climbs higher than RN_1's MC (such as at time 100s), it starts to lose market and it has to cut its price, which is similar to Experiment (1,2,1). However, one important difference is that RN_2 still keeps client 6 and 7, which allows RN_2 to finish its hill-climbing approximately at time 200s. If there were no competition from RN_1, RN_2 would have ended up at a higher price. To let RN_2 finish at the highest possible price, we let RN_2 climb again after a certain period. Figure 9 shows that RN_2 eventually climbs to a price close to RN_1's MC (which is the second lowest MC). Compared to Scenario 2 and 3, converging to the second lowest MC is much more difficult and requires a lengthy probing process, during which the wining RN loses certain profit it could have acquired. Therefore, this underscores the importance of keeping communication among the RNs.

TABLE VI
SIMULATION PARAMETERS IN EXPERIMENT (1,3,4)

Cost of RN 1-3	1.02, 0.08, 2.10
W of client 4-7	0.008, 0.012, 0.016, 0.028

D. Summary of Results and Additional Comments

We evaluate the pricing mechanisms in different network scenarios. In Scenario 1, we show that the proposed

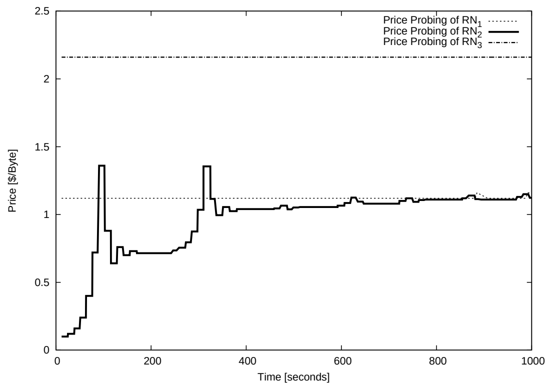

Fig. 9. Concurrent price probing in Experiment (1,3,4).

hill-climbing algorithm is reasonably quick and can converge very closely to the optimal value. In Scenario 2 and 3, we show that the VCG-like second lowest MC pricing mechanism can determine the market price instantly without going through the hill-climbing process. In Scenario 4, we show that a concurrent hill-climbing process can reach approximately the second lowest MC at equilibrium. To maintain stable pricing, it is beneficial for the RNs to keep communication among them.

V. Related Work

Our work in this paper is related to the following research areas: 1) multihop wireless hotspot network, 2) multihop cellular network, 3) cooperation in multihop ad hoc network (MANET), and 4) algorithmic mechanism design in distributed systems. Below we discuss the related work in each of these areas.

Multihop wireless hotspot network [1]–[4] has been recently proposed to extend the coverage area of a base station, especially when using a high-rate short-range radio such as IEEE 802.11a. In [3], an enhanced MAC layer protocol is designed to increase multihop performance by using multiple channels. In [4], transport layer mechanisms are designed to achieve end-to-end throughput and delay assurances via service differentiation. All these studies have focused on improving system performance, but have not considered the incentive problem of packet forwarding. Therefore, our work in this paper can be considered as a pilot study in this direction.

A multihop cellular network [5]–[9] is similar in concept to the multihop hotspot network. However, the base stations in a multihop cellular network are usually owned by a single operator and can be *trusted*. All the mobile terminals belong to the *same* cellular provider, and the provider can reward the terminals for multihop packet forwarding. In [7] a probabilistic charging scheme is designed to reduce the overhead of repeated micro-payments, while in [8] the charge is based on a session to further reduce the charging overhead. In [9] security mechanisms are designed to protect the authenticity of the forwarding path in order to ensure accurate accounting and payments. All these schemes require the cellular base station to act as a trusted party. However, in a spontaneous multihop hotspot network, the wireless base station does not have any business relationship with the mobile clients. The mobile clients may not be customers of the hotspot network provider. Therefore, we cannot rely on the wireless base station to collect payments. Instead, we model the multihop system as a market involving the relaying nodes, which is a more general model than the existing models for multihop cellular network.

Similar to multihop hotspot and cellular networks, cooperation in a multihop ad hoc network (MANET) is very important. Its impact has been quantitative studied in [26]. As mentioned in Section II-A, the existing approaches include game theory based approach [10]–[16] and credit (or micro-payment) based approach [17]–[20]. In [17] and [18], a tamper-resistant hardware module is used to enforce the charging and crediting of packet forwarding, while in [19] a software-based charging scheme is designed such that cheating is not desirable. In [20], a charging scheme is proposed based on an auction model at each router. Our work in this paper differs from [20] in two important aspects: 1) our scheme in this paper allows selecting different relaying nodes for packet forwarding, while in [20] only a pre-set multihop path is allowed; and 2) our scheme in this paper considers the whole network as a market, while in [20] the market is contained within each router since a MANET-wide market will have to involve heavy multihop signaling overheads.

Finally, the recent development of many new types of distributed systems often involves self-interested parties over the network, such as peer-to-peer resource sharing, ad hoc networks, pervasive computing, computational grids and overlay networks. As a result, the concept of *truthful* or *strategy-proof* computing has been proposed to stimulate each participant to follow a prescribed protocol without deviation via algorithmic mechanism designs [25], [27]–[30]. For example, a VCG-based mechanism has been utilized for BGP routers [31] and MANET routing [32]. In this paper, the second lowest marginal cost pricing mechanism (in Section III-C) is another example of using algorithmic mechanism design in a distributed system with selfish agents.

VI. Conclusion

In this paper we focus on the packet forwarding incentive problem in a two-hop wireless hotspot network. We adopt the credit (or micro-payment) based incentive approach, i.e., the clients pay the relaying nodes for their packet forwarding service. We model the system as a market where the pricing for packet forwarding is determined by demand and supply. We classify the network into four different scenarios, and propose different pricing solutions for each of them. In particular, we design a hill-climbing algorithm for a monopoly market, and introduce a VCG-like second lowest marginal cost pricing mechanism for a market with multiple relaying nodes which guarantees truthful reporting of marginal costs. We further extend the network scenarios to cover the situation where a client can only reach a subset of the relaying nodes, and another situation where the relaying nodes do not have communication among them. Our simulation results show that the pricing mechanisms are able to guide the market into an equilibrium state quickly. Our analysis in this paper underscores the importance of keeping communication among the relaying nodes, therefore, the base station should be encouraged to act as intermediate to reliably relay pricing messages among them.

Appendix I
Hill-Climbing Algorithm in Scenario 1

In this section we discuss in detail the hill-climbing algorithm to find an optimal price to maximize RN's profit. Our algorithm is a general algorithm which does not rely on the exact shape of the profit function, as long as the function has a single "peak". Before starting, the RN needs to specify an accuracy threshold Δ $(\Delta \geq 0)$ to serve as the condition to terminate the algorithm. Our algorithm consists of the following two stages.

The first stage performs a coarse but fast probing to locate a price region where $\mathcal{P}$ should belong to. The incremental step size d is *doubled* each time to quickly encompass the optimal price. The algorithm starts at the RN's marginal cost. It stops when the profit starts to decrease, i.e., it has crossed the "peak" of the profit function. During the searching process, the algorithm maintains three prices: P_1, P_2 and P_3, where $P_1 < P_2 < P_3$ and $Profit(P_1) < Profit(P_2) < Profit(P_3)$. [9] When the first stage terminates, the following conditions should hold: $Profit(P_1) < Profit(P_2)$, $Profit(P_3) < Profit(P_2)$, and $\mathcal{P} \in (P_1, P_3)$. At the end of this stage, it can only have one of the following two possibilities

[9]For simplicity, it is assumed that $C + \Delta < \mathcal{P}$.

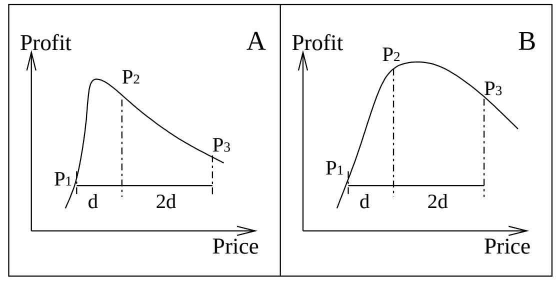

Fig. 10. Two possibilities after the first stage.

(shown in Figure 10): either $P_2 \geq \mathcal{P}$ (Case A) or $P_2 < \mathcal{P}$ (Case B). The next stage will try to narrow down the target price region (P_1, P_3) using P_2 as the pivot. Pseudo-code of the first stage is shown in Table VII.

TABLE VII
First Stage of Hill-Climbing

```
/* Stage 1 */
d ← Δ ;
P1 ← C ; /* start from the cost */
P2 ← P1 + d ;  d ← d × 2 ;
P3 ← P2 + d ;  d ← d × 2 ;
while (Profit(P3) > Profit(P2)) {
    P1 ← P2 ;
    P2 ← P3 ;
    P3 ← P2 + d ;  d ← d × 2 ;
}
```

The second stage searches the price region (P_1, P_3) by first checking the mid-point P_m of P_1 and P_3 ($P_m = \frac{P_1+P_3}{2}$). Suppose $P_m > P_2$ (the case of $P_m < P_2$ is similar). If $Profit(P_m) > Profit(P_2)$, use P_2 to replace P_1 and P_m to replace P_2; otherwise, use P_m to replace P_3. That is, the algorithm always maintains the following conditions: $P_1 < P_2 < P_3$, $Profit(P_1) < Profit(P_2)$, $Profit(P_3) < Profit(P_2)$, and $\mathcal{P} \in (P_1, P_3)$. In case $P_m = P_2$, we choose P_m to be the one-third point between P_1 and P_3 ($P_m = \frac{2\times P_1+P_3}{3}$). This *binary* search process repeats until the target region is smaller than the pre-set accuracy threshold ($P_3 - P_1 \leq \Delta$). Pseudo-code of the second stage is shown in Table VIII.

In summary, the first stage of hill-climbing performs a coarse but fast search to locate the price region where the optimal price should belong to. The step size is doubled each time to accelerate the process. In the second stage, a binary search is conducted using a pivot (P_2) to narrow down the target price region. The program stops when the pre-set accuracy threshold is reached.

As an example, for a demand curve with $C = 0.08$, $W = 0.008$, and $\Delta = 0.001$, the hill-climbing algorithm reaches its optimal price 3.16233 after 28 steps, which is very close to the theoretical optimal value of 3.16228.

TABLE VIII
SECOND STAGE OF HILL-CLIMBING

```
/* Stage 2 */
while (P_3 − P_1 > Δ) {
    P_m ← (P_1 + P_3)/2 ;
    if (P_m > P_2) {
        if (Profit(P_m) ≤ Profit(P_2)) {
            P_3 ← P_m ;
        }
        else {
            P_1 ← P_2 ;
            P_2 ← P_m ;
        }
    }
    else {
        if (P_m == P_2) {
            P_m ← (2 × P_1 + P_3)/3 ;
        }
        if (Profit(P_m) ≤ Profit(P_2)) {
            P_1 ← P_m ;
        }
        else {
            P_3 ← P_2 ;
            P_2 ← P_m ;
        }
    }
}

𝒫 ← P_2 ;
```

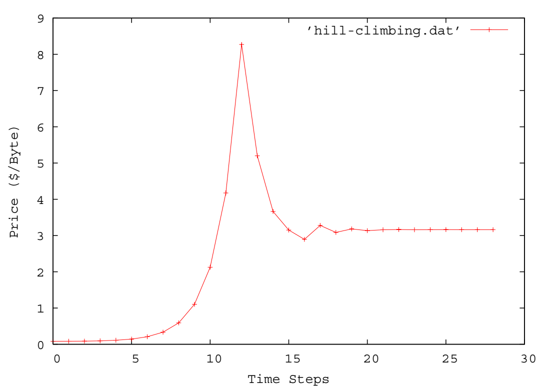

Fig. 11. Example of a hill-climbing process.

In fact, the price is already very close to the optimal value after 19 steps (see Fig. 11). The figure also clearly shows the fast probing (in the first stage from time 0 to 12) and quick converging (in the second stage from time 13 to 28) properties of our algorithm.

ACKNOWLEDGMENTS

This work was supported by the DoD Multi-disciplinary University Research Initiative (MURI) program administered by the Office of Naval Research under Grant N00014-00-1-0564, and the NSF EIA 99-72884EQ grant. Any opinions, findings, and conclusions are those of the authors and do not necessarily reflect the views of the above agencies.

REFERENCES

[1] Y.-D. Lin, Y.-C. Hsu, K.-W. Oyang, T.-C. Tsai, and D.-S. Yang, "Multihop wireless IEEE 802.11 LANs: A prototype implementation," in *Proc. IEEE Intl. Conf. on Communications (ICC'99)*, Vancouver, Canada, June 1999.

[2] A. Balachandran, G.M. Voelker, and P. Bahl, "Wireless hotspots: Current challenges and future directions," in *Proc. The First ACM Intl. Workshop on Wireless Mobile Applications and Services on WLAN Hotspots (WMASH'03)*, San Deigo, California, U.S.A., Sept. 2003.

[3] F. Fitzek, D. Angelini, G. Mazzini, and M. Zorzi, "Design and performance of an enhanced IEEE 802.11 MAC protocol for multihop coverage extension," *IEEE Wireless Communications*, Dec. 2003.

[4] K.-C. Wang and P. Ramanathan, "End-to-end throughput and delay assurances in multihop wireless hotspots," in *Proc. The First ACM Intl. Workshop on Wireless Mobile Applications and Services on WLAN Hotspots (WMASH'03)*, San Deigo, California, U.S.A., Sept. 2003.

[5] Y.-D. Lin and Y.-C. Hsu, "Multihop cellular: A new architecture for wireless communications," in *Proc. IEEE INFOCOM 2000*, Tel-Aviv, Israel, Mar. 2000.

[6] G.N. Aggelou and R. Tafazolli, "On the relaying capacity of next-generation GSM cellular networks," *IEEE Personal Communications Magazine*, vol. 8, no. 1, Feb. 2001.

[7] M. Jakobsson, J.-P. Hubaux, and L. Buttyan, "A micro-payment scheme encouraging collaboration in multi-hop cellular networks," in *Proc. of the 7th Intl. Financial Cryptography Conference (FC'03)*, Gosier, Guadeloupe, Jan. 2003.

[8] N.B. Salem, L. Buttyan, J.-P. Hubaux, and M. Jakobsson, "A charging and rewarding scheme for packet forwarding in multi-hop cellular networks," in *Proc. of the 4th ACM Symp. on Mobile Ad Hoc Network and Computing (MobiHoc'03)*, Annapolis, Maryland, U.S.A., June 2003.

[9] H. Luo, R. Ramjee, P. Sinha, L. Li, and S. Lu, "UCAN: A unified cellular and ad-hoc network architecture," in *Proc. ACM/IEEE International Conference on Mobile Computing and Networking (MobiCom'03)*, San Diego, California, U.S.A., Sept. 2003.

[10] S. Marti, T.J. Giuli, K. Lai, and M. Baker, "Mitigating routing misbehavior in mobile ad hoc networks," in *Proc. 6th ACM/IEEE Annual Intl. Conf. on Mobile Computing and Networking (MobiCom 2000)*, Boston, Massachusetts, U.S.A., Aug. 2000.

[11] S. Buchegger and J.-Y. Le Boudec, "Performance analysis of the CONFIDANT protocol," in *Proc. 3rd ACM Intl. Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc 2002)*, Lausanne, Switzerland, June 2002.

[12] P. Michiardi and R. Molva, "CORE: A collaborative reputation mechanism to enforce node cooperation in mobile ad hoc networks," in *Proc. 6th IFIP Conf. on Security Communications and Multimedia (CMS 2002)*, Portoroz, Slovenia, Sept. 2002.

[13] P. Michiardi and R. Molva, "A game theoretical approach to evaluate cooperation enforcement mechanisms in mobile ad hoc networks," in *Proc. Workshop on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks (WiOpt'03)*, INRIA Sophia-Antipolis, France, Mar. 2003.

[14] M. Felegyhazi, L. Buttyan, and J.-P. Hubaux, "Equilibrium analysis of packet forwarding strategies in wireless ad hoc networks - the static case," in *Proc. 8th International Conference on Personal Wireless Communications (PWC 2003)*, Venice, Italy, Sept. 2003.

[15] A. Urpi, M. Bonuccelli, and S. Giordano, "Modeling cooperation in mobile ad hoc networks: a formal description of selfishness," in *Proc. Workshop on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks (WiOpt'03)*, INRIA Sophia-Antipolis, France, Mar. 2003.

[16] V. Srinivasan, P. Nuggehalli, C. F. Chiasserini, and R. R. Rao, "Cooperation in wireless ad hoc networks," in *Proc. INFOCOM 2003*, San Francisco, California, U.S.A., March-April 2003.

[17] L. Buttyan and J.-P. Hubaux, "Enforcing service availability in mobile ad hoc WANs," in *Proc. 1st ACM Workshop on Mobile Ad Hoc Networking and Computing (MobiHoc 2000)*, Boston, Massachusetts, U.S.A., Aug. 2000.

[18] L. Buttyan and J.-P. Hubaux, "Stimulating cooperation in self-organizing mobile ad hoc networks," *ACM/Kluwer Mobile Networks and Applications (MONET)*, vol. 8, no. 5, Oct. 2003.

[19] S. Zhong, J. Chen, and Y.R. Yang, "Sprite: A simple, cheat-proof, credit-based system for mobile ad hoc networks," in *Proc. INFOCOM 2003*, San Francisco, California, U.S.A., March-April 2003.

[20] K. Chen and Klara Nahrstedt, "iPass: an incentive compatible auction scheme to enable packet forwarding service in MANET," in *Proc. of the 24th IEEE International Conference on Distributed Computing Systems (ICDCS 2004)*, Tokyo, Japan, Mar. 2004.

[21] A. Agliari, L. Gardini, and T. Puu, "Global bifurcations of basins in a triopoly game," *International Journal of Bifurcation and Chaos*, vol. 12, no. 10, pp. 2175–207, 2002.

[22] W. Vickrey, "Counter-speculation, auctions, and competitive sealed tenders," *The Journal of Finance*, vol. 16, no. 1, pp. 8–37, Mar. 1961.

[23] E.H. Clarke, "Multipart pricing of public goods," *Public Choice*, vol. 11, pp. 17–23, 1971.

[24] T. Groves, "Incentives in teams," *Econometrica*, vol. 41, no. 4, pp. 617–631, July 1973.

[25] N. Nisan and A. Ronen, "Algorithmic mechanism design," in *Proc. 31st ACM Symp. on Theory of Computing (STOC 99)*, Atlanta, Georgia, U.S.A., May 1999, pp. 129–140.

[26] B. Lamparter, M. Plaggemeier, and D. Westhoff, "Poster: About the impact of co-operation approaches for ad hoc networks," in *Proc. of the 4th ACM Symp. on Mobile Ad Hoc Network and Computing (MobiHoc'03), Poster Session*, Annapolis, Maryland, U.S.A., June 2003.

[27] H.R. Varian, "Economic mechanism design for computerized agents," in *Proc. USENIX Workshop on Electronic Commerce*, New York, NY, U.S.A., July 1994.

[28] J. Feigenbaum and S. Shenker, "Distributed algorithmic mechanism design: recent results and future directions," in *Proc. 6th ACM Intl. Workshop on Discrete Algorithms and Methods for Mobile Computing and Communications (DIALM 2002)*, Atlanta, Georgia, U.S.A., Sept. 2002.

[29] C. Ng, D.C. Parkes, and M. Seltzer, "Strategyproof computing: System infrastructures for self-interested parties," in *Proc. 1st Workshop on Economics of Peer-to-Peer Systems*, Berkeley, California, U.S.A., June 2003.

[30] X.-Y. Li and W.-Z. Wang, "Truthful computing in wireless networks," in *Resource Management in Wireless Networking*, M. Cardei, I. Cardei, and D.-Z. Du, Eds. Kluwer Academic Publishers, The Netherlands, 2004.

[31] J. Feigenbaum, C. Papadimitriou, R. Sami, and S. Shenker, "A BGP-based mechanism for lowest-cost routing," in *Proc. 21st ACM Symp. on Principles of Distributed Computing (PODC 2002)*, Monterey, California, U.S.A., July 2002.

[32] L. Anderegg and S. Eidenbenz, "Ad hoc-VCG: A truthful and cost-efficient routing protocol for mobile ad hoc networks with selfish agents," in *Proc. ACM/IEEE International Conference on Mobile Computing and Networking (MobiCom'03)*, San Diego, California, U.S.A., Sept. 2003.

[33] H. Tewari and D. O'Mahony, "Multiparty micropayments for ad hoc networks," in *Proc. IEEE Wireless Communication and Networking Conference (WCNC)*, New Orleans, LA, U.S.A., Mar. 2003.

[34] H. Tewari and D. O'Mahony, "Real-time payments for mobile IP," *IEEE Communications Magazine*, Feb. 2003.