Pricing Reliable Routing in Wireless Networks of Selfish Users*

Hua Liu† and Bhaskar Krishanamachari†‡
Department of Computer Science† and Electrical Engineering‡
University of Southern California, Viterbi School of Engineering
{hual,bkrishna}@usc.edu

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We examine incentives for cooperative reliable routing in wireless ad hoc networks where the users may be inherently selfish. In our game-theoretic formulation, each node on the selected route from a source to a destination receives a payoff that is proportional to the product of a source-defined-price and the probability that a given packet can be delivered to the desired destination, minus the corresponding communication cost. Although prior work has suggested that this problem may be NP-hard, we give a polynomial-time construction for deriving a Nash equilibrium path in which no route participant has incentive to cheat. Via simulations using realistic wireless topologies, we find that there is a critical price threshold beyond which an equilibrium path exists with high probability. Further, we show that there exists an optimal price setting beyond the price threshold at which the source can maximize its utility. We examine how these thresholds and price settings vary with node density for different node reliability models.

1 Introduction

Game theory provides tools for analyzing the behavior of inherently selfish players in a different systems. Although initially developed to model the behavior of humans in economic settings, it is now increasingly recognized as perhaps an even more appropriate tool for truly "rational" computer agents serving selfish users. These techniques are particularly applicable in the context of mobile ad hoc and mesh networks in which nodes corresponding to different users need to be provided incentives for carrying data belonging to other nodes in the network, as this activity on behalf of others costs valuable bandwidth and energy resources.

We consider a reliable routing game for wireless networks of selfish users that is essentially similar to the game-theoretic models proposed and investigated by Kannan, Sarangi, and Iyengar [1, 2, 3, 4], with modifications to incorporate an explicit notion of pricing. In our model, nodes in the network forward packets with a known probability. Each link uses ACK-based retransmissions (simple ARQ) to provide guaranteed delivery and therefore has a distinct transmission cost that depends upon the link quality. The end-to-end probability of packet delivery on any path from a given source to destination is hence the product of the node forwarding probabilities. The source provides a virtual "payment" to each node on the path for each packet that is successful delivered to the destination.

For each packet forwarded, the payoff for each routing node is therefore the difference between the payment it receives from the source and its cost of transmitting that packet. Nodes agree to participate in a routing path only if their payoff is positive. The source accepts a route only if its expected benefit

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from the delivery of a packet (which depends upon the value of the information being delivered) exceeds the payment to participating routers in addition to the cost of transmitting the packet to the first relay node. Moreover, it is important for the source to find a stable route configuration, where no participating routing node has an incentive to change its next hop link. Such a stable configuration corresponds to a Nash equilibrium for the game.

The following are the key contributions and findings of our work:

- In the work by Kannan *et al.*, it is claimed that the complexity of determining and computing a Nash Equilibrium for the closely related reliable routing game that they present is NP-hard. However, we are able to show in this work that the existence of a Nash Equilibrium path can in fact be determined in polynomial time, through an algorithm that is a modification of the Dijkstra technique.

- It is intuitive that the likelihood of finding a Nash equilibrium in which selfish nodes are happy to participate in routing should increase with an increase in the price offered to them as payment. However, through realistic simulations, we find additionally that in fact there exists a critical threshold price beyond there is a high probability that such an equilibrium path exists, when considering random wireless network configurations of fixed density. The existence of such a critical threshold has practical significance as it implies that a fixed price can be used as incentive in the case of mobile networks where specific configurations change continuously.

- We also find that there exists an optimum price at which the source can maximize its utility.

- We evaluate how the critical price threshold and the source-utility-maximizing price vary with network density and the value of the information to the source.

The rest of the paper is organized as follows. We briefly discuss related work in section 2, before giving details of the reliable routing game in section 3. We present the polynomial time algorithm for determining the Nash Equilibrium path in section 4. We then use realistic simulations to demonstrate the existence of critical threshold prices and utility-optimal prices, and to evaluate their dependence on network and application parameters in section 5. Finally, we present concluding comments in section 6.

2 Related Work

The problem of obtaining cooperative routing behavior in wireless ad hoc networks consisting of inherently selfish nodes has received considerable attention in recent years. Two main avenues of research in this regard are (a) reputation and punishment-based techniques and (b) pricing and payment-based techniques.

Reputation-based techniques provide mechanisms to track the behavior of nodes and punish those that behave in a selfish manner. Along these lines, Marti *et al.* [6] present the watchdog and path-rater mechanisms that punish nodes which don't relay packets correctly; the CONFIDANT protocol [7, 8] and the CORE mechanism [22] are also distributed reputation systems that seek to identify and deal with misbehaving nodes. The OCEAN mechanism [9] seeks to obviate some of the complexity associated with second-hand reputation exchange-based schemes by relying on first-hand observations alone. Srinivasan *et al.* [18], provide a formal game-theoretic framework for reputation/punishment and show that the generous tit-for-tat mechanism can be used to obtain Nash equilibria that converge to Pareto optimal, rational solutions. Equilibrium conditions obtained using similar generous tit for tat strategies taking into account the multihop network topology for static and dynamic scenarios are investigated in [12, 13]. Altman *et al.* advocate a less aggressive punishment policy to improve performance [14]. Urpi *et al.* [10] and Nurmi [17] model the situation as dynamic Bayesian games, which allow effective use of prior history in enforcing cooperation.

The alternative to enforcing cooperation is providing nodes with an incentive to cooperate through payment and pricing mechanisms. Buttyan and Hubaux introduce the notion of NUGLETS, a form of virtual currency that provide an incentive for nodes to cooperate [16]. The use of pricing to obtain incentives for cooperation is also advocated in the works by Crowcroft *et al.* [21] and Ileri *et al.* [15]. In all these schemes, nodes which forward data for others receive credits that can be used to pay others to carry their own data. DaSilva and Srivastava [11] study the tradeoffs between cost and benefit in a game theoretic context to determine how they impact cooperation. Our work can be viewed as closely related to these approaches, as we too provide incentive to the intermediate nodes to cooperate in the routing through the payment offered by the source node, and evaluate the impact of pricing upon cooperation and the utility provided to the source.

With payment-based schemes, however, there is an associated risk of cheating due to false claims by nodes trying to obtain payments they do not deserve. While we do not explicitly tackle this issue in our work, researchers have proposed solutions for handle this potential abuse. The micropayment scheme presented in [20] incorporates an audit mechanism to prevent false claims. SPRITE is another cheat-proof mechanism that uses a credit clearance server to provide payments to nodes for cooperation. Anderegg and Eidenbenz [19] propose the use of the Vickrey-Clark-Groves mechanism to obtain truthful claims for payments.

Our investigations are motivated by the works of Kannan, Sarangi and Iyengar on reliable query routing [1, 2, 3, 4]. They are the first to formulate a game where the node utilities show a tension between path reliability and link costs, and they have considered different interesting variants of this problem. One difference in our work is that we modified the notion of value of information in their work to an adjustable price offered by the source, and modified the source payoff to include this payment. This allows to evaluate how pricing impacts the cooperation of nodes. However, our work directly contradicts the claim in [1, 2, 3, 4] that the problem of determining the Nash equilibrium path under such a formulation is NP-hard. We find flaws in the proofs presented in [3, 4]. For one, the authors claim the problem is not even in NP. Given a particular path as a certificate, it can be verified first in $O(n^2)$ time that it has positive payoff for all nodes. Then, to consider the possible choices for defection for any given node (keeping the strategy of all other nodes in the network the same, as per the definition of Nash equilibrium), it suffices to consider having it connect to each of the other nodes ahead of it on the path, and see whether those shortcuts can improve its payoff and give it an incentive to defect. Doing this $O(n)$ verification procedure for each node on the path takes a total of $O(n^2)$ time. Hence the problem is in NP. Further, the proof in [3, 4] attempts to prove NP hardness by reducing the problem from Hamiltonian path. However, there is a confusion in the proof introduced by the fact that in their particular graph construction the shortest positive payoff paths happen to be Hamiltonian (visits all nodes). Even with the traditional simple minimum cost path problem solved using the Dijkstra's algorithm, it can happen for *certain* graphs that the minimum length path between a pair of nodes happens to visit all other nodes in the network. This does not make the shortest path problem (which is in P) equivalent or harder in complexity than finding a Hamiltonian path in *any arbitrary* graph (which is NP-complete).

3 Payoff and Utility Functions

Energy saving is fundamental important to routing in wireless ad hoc networks. The problem considered in this work also considers the challenge of node reliability. For each packet being forwarded by a given node i, there is assumed to be a known probability R_i that that node is able to reliably forward this packet. The original works on sensor-centric reliable query routing [1, 2, 3, 4] consider probabilistic node failure. Another interpretation is, in the context of real-time traffic, to think of the packet as having a strict deadline and being dropped forcibly when facing delay, such as when the node is busy with other activity (processing, communication) or if it is sleeping. The quantity $1 - R_i$ then represents a per-node drop probability for packets with strict deadlines in a real-time stream.

We assume in the following that all nodes in the network are driven by their own self-interests as defined by their corresponding payoffs. The payoff models we use involve a tradeoff between path reliability and energy consumption for each node.

In each game, a source node (src) holds a piece of information with value D and wants to send it to a particular destination node (dst). The source node will offer a price p, indicating the payment to be made to each routing node v_i for $i = 1, 2, ...n$ on a given path $\mathtt{P} = (src, v_1, v_2, ..., v_n, dst)$. A node on the path will participate in the routing only if its payoff is positive. Among all the feasible paths, the source will choose the one that maximizes its own expected payoff after it pays all the routing nodes.

Let R_i denotes the reliability for each routing node v_i, and $C_{i,j}$ denotes the link set up cost between node v_i and v_j. The payoff function of the routing node v_i in path $\mathtt{P}$ is defined as the production of the onward path reliability and the price paid by the source node minus the link set up cost between v_i and its next hop v_{i+1}.

$$U(v_i, p) = p \times \prod_{k=i}^{n} R_k - C_{i,i+1}$$

The strategy for each intermediate node is to chose whether to forward this information or not, and who to forward to, based on the price provided by the source. Only if it can profit from forwarding the information, will it participate in the routing, and it will try to maximize its payoff by choosing the appropriate next hop.

The gain or utility for the source node in this routing game is defined as following:

$$U(src, D, p) = (D - n \times p) \times \prod_{k=1}^{n} R_k - C_{src,1}$$

The source utility/gain relies on the value of expected profit for complete routing the information to the destination minus the cost for source set up link with the first hop. The source's goal is to maximize its gain based on all the bids provided by the intermediate nodes. The destination node does not participate in the routing game, and simply receives whatever information is sent to it.

4 Computing the Nash equilibrium

In Game theory, the Nash equilibrium is an important solution concept that represents a stable outcome for a game involving selfish users. A Nash equilibrium is a set of strategies, one for each player, such that no player has incentive to unilaterally change his/her action. Players are in equilibrium if a change in strategies by any one of them would lead that player to earn less than if she remained with her current strategy.

In this section, we first introduce the formal definition of positive payoff path. After that, a polynomial construction for finding a positive payoff path is presented. Furthermore, we prove that using this algorithm, the outcome path is a Nash equilibrium path.

Definition 1 *A path $\mathtt{P} = (src, v_1, v_2, ..., v_n, dst)$ is a Positive Payoff Path (PPP) with respect to a payoff function $U(v_i, p)$ if and only if for all the intermediate nodes $v_i (i = 1, 2, ...n)$, the payoff function $U(v_i, p) > 0$. $\mathtt{P}$ is a Negative Payoff Path (NPP) if $\forall v_i, U(v_i, p) < 0$.*

To find a positive payoff path, we first simplify the problem to a more concise representation. According to the definition, we need for each intermediate routing node v_i, $U(v_i, p) > 0$. It equals to

$$\prod_{k=i}^{n} R_k > \frac{C_{i,i+1}}{p}$$

To convert the production to summation, we take logarithm for both side and get

$$\sum_{k=i}^{n} log R_k > log \frac{C_{i,i+1}}{p}$$

. Notice that $0 \leq R_k \leq 1$, we take the inverse of each R_k to make each term in the summation positive. The original formula now transform to

$$\sum_{k=i}^{n} log \frac{1}{R_k} < \frac{p}{C_{i,i+1}}$$

for each v_i. Replacing $log \frac{1}{R_k}$ by r_k ($r_k \geq 0$) and replacing $\frac{p}{C_{i,i+1}}$ by $c_{i,i+1}$, we formulate the problem of finding a PPP in the original graph to an equal problem of finding an NPP in a transformed network graph, where each node has a positive value r_i and each edge is assigned a value $c_{i,j}$, according to utility function

$$U^{-1}(v_i, p) = \sum_{k=i}^{n} r_k - c_{i,i+1}$$

A polynomial time algorithm modified from Dijkstra's algorithm can be applied to find the NPP in the given graph. Figure 1 depicts the algorithm to find the NPP for a node v_i to destination (denotes this v_i as *src* in the algorithm). In brief, the algorithm starts labeling nodes from the destination, applying Dijistra's algorithm, with adding negative utility checking step. In the algorithm, each node has a label which is a tuple $(from, l(v_i), U^{-1})$. The first item in the tuple indicates from which node the label comes, i.e., the next hop of current node starting from source. The second term in the tuple records the summation of r_k, which is analogous to the length in Dijistra's algorithm. The third term tracks the current U^{-1} value. Since the r value is related to nodes instead of the links, we need a definition of neighborhood set for a given graph $G(V, E)$.

Definition 2 Given a graph $G(V, E)$, $I \subset V$,$S \subset V$, S is the neighborhood set of I (denote as $N(I)$) if and only if $\forall j \in S$, $j \notin I \bigwedge \exists i \in I$ such that $(i, j) \in E$

Finding An NPP in Transformed Network Graph

1. *Initialize:* Feasible set $FS = \{dst\}$, all other nodes labeled as $(-, \inf, -)$
2. *Label:* if starting node $src \in FS$ or $N(FS) = \varnothing \wedge src \notin FS$, program terminates. Otherwise, for every node $v_i \in N(FS)$
   - *try step*: try to change the node's second term in the label to $l(v_i) = \min_{v_j \in FS \wedge (i,j) \in E} (l(v_i), l(v_j) + r_i)$
   - *check step*: if $U^{-1}(v_i, p) = l(v_i) - c_{i,j} < 0$, label change is successful and node v_i gets new label; otherwise delete the corresponding edge (i, j), go to *re-try step*
   - *re-try step*: if ($\exists k \in FS$ such that $(i, k) \in E$, go to try step; otherwise, keep v_i's label unchanged, continue;
3. *Expand:* choose $\min_{v \notin FS} l(v)$, record its corresponding next hop and U^{-1}. We say this node has completed labeling. Add this node into set FS, go to Step 2 (*Label*).

Figure 1: Polynomial time algorithm to find a Negative Payoff Path in transformed network graph

Lemma 1 *Given graph $G(V, E)$, if $(i, j) \in E$ is deleted in some step in the Algorithm, (i, j) does not lie in any NPP from src to dst in the original graph $G(V, E)$.*

Proof: (by contradiction) Assume that there is a link (i, j) between nodes $v_i \notin FS$ and $v_j \in FS$

deleted in some iteration lies in an NPP path P = $(v_1, ..., v_i, v_j, ..., v_n)$. To clarify our claim, we now assume that edge (i, j) is the first link we delete during the algorithm (It can be easily extended to the case where (i, j) is not the first link to be deleted since the graphs before and after deleting an edge are exactly same when considering NPP problem.) Since P is an NPP, we have $\sum_{k=i}^{n} r_k < c_{i,j}$, i.e. $\sum_{k=j}^{n} r_k + r_i < c_{i,j}$. Recall that in the algorithm, we check U^{-1} for trying to label v_i as $\min_{v_j \in FS \wedge (i,j) \in E} (l(v_i), l(v_j) + r_i)$. And for node v_j, $l(v_j)$ is the minimum summation of r values from node v_j onwards since v_j is in the feasible set. Hence, we have

$$\sum_{k=j}^{n} r_k + r_i \geq l(v_j) + r_i \geq min(l(v_i), l(v_j) + r_i)$$

It follows $min(l(v_i), l(v_j) + r_i) < c_{i,j}$. Then, according to the algorithm, edge (i, j) should not be deleted. This contradicts the assumption. Thus edge (i, j) does not lie in any NPP from *src* to *dst* in $G(V, E)$. □

Theorem 1 The algorithm to find an NPP path in the transformed network graph is correct.

Proof: **(Soundness)**: the path found by the algorithm in the transformed graph is guaranteed to be an NPP path since it has a check step to make sure each node in the feasible set has a negative payoff.

(Completeness): We need to prove that if there exists an NPP in the graph, the algorithm will return one. According to Lemma 1, since the edge deleted in the algorithm doesn't lie in any NPP, the algorithm doesn't destroy any NPP path in the graph. The algorithm terminates only under two conditions: either it finds the NPP or $N(FS) = \varnothing \wedge src \notin FS$. The latter case indicates that the source and destination are separated into two isolated parts of the graph, which implies that there is no NPP in the original given graph. □

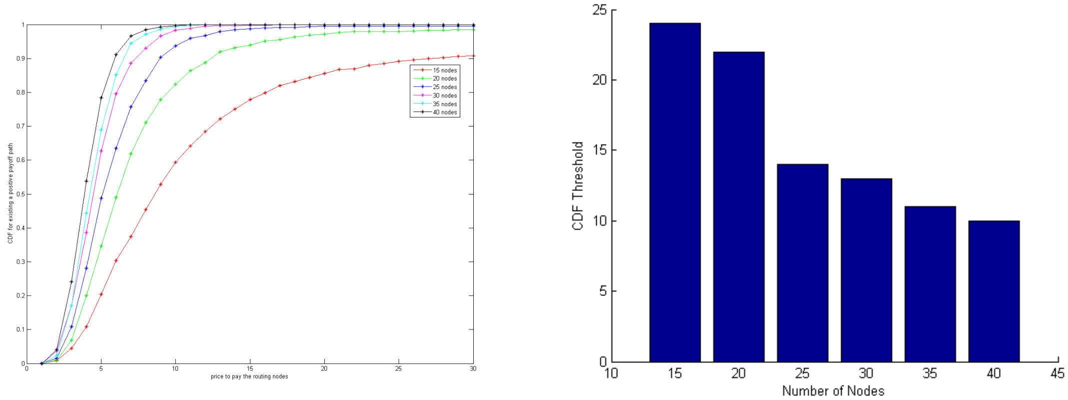
The computational complexity of the algorithm is polynomial. The Dijkstra's algorithm can be run in time $O(n^2)$. For each edge deletion in our algorithm, we need to retry the labeling, which will cost at most extra $O(n)$ time for each node. So the running time of our algorithm is bounded by $O(n^3)$.

Notice that when mapping the algorithm back to the PPP problem, we always choose the most reliable path among all the feasible paths. In the algorithm we keep adding the nodes with minimum summation of r that still satisfies the negative utility constraints. This observation can be used to prove that path returned by this algorithm is a Nash equilibrium path.

Theorem 2 The path found by the algorithm is a Nash equilibrium path in the PPP finding problem.

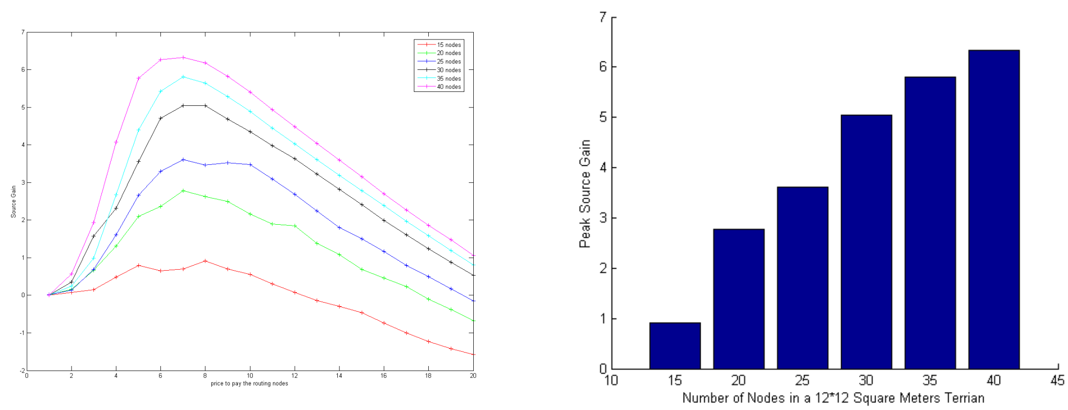
Proof (by contradiction): Assume that the algorithm returns a path P $= (v_1, v_2, ..., v_i, v_{i+1}, ..., v_j, ...v_n)$ which is not a Nash equilibrium. Without loss of generality, suppose only one node v_i wants to switch his next hop from v_{i+1} to v_j, where $j > i + 1$ (there is no motivation to switch the next hop to a node that not on the forward path as this would disconnect that node from the source giving 0 payoff). Path $\hat{\mathrm{P}} = (v_0, v_1, ..., v_i, v_j, ..., v_n)$ is also a PPP, since the payoff of the nodes before v_j increases by the increase of path reliability (remember $0 \leq R_k \leq 1$) and the payoff after v_j (including v_j) keep unchanged. Thus path $\hat{\mathrm{P}}$ is one of the feasible paths. Since the path abandoned some intermediate nodes, the path reliability of $\hat{\mathrm{P}}$ is larger than P. This would imply that the algorithm should return path $\hat{\mathrm{P}}$ instead of P, which contradicts the assumption. □

As we mentioned before, the algorithm is run to obtain a positive payoff path to destination from each neighbor of the source node. Among all the feasible paths reported from its set of neighbors, the source node picks the one that gives its maximum profit according to the source's utility function (which incorporates the value to the source and the payment made to all nodes on the path in addition to the path reliability and the cost of transmission).



(a) (b)

Figure 2: The probability that a positive payoff equilibrium path exists as a function of the price offered by the source and the 90% critical price threshold as a function of density (for correlated reliability model)



(a) (b)

Figure 3: Source utility as a function of offered price, and Peak source utility as a function of density (for correlated reliability model)

5 Evaluation of Price Selection

We now turn to a set of realistic simulations, to evaluate how pricing impacts the existence of Nash equilibrium paths and the source utility.

5.1 Simulation Experimental Setup

By using a realistic lossy wireless topology generator [24], we simulate 1000 graphs for each case, keeping all radio and environment parameters to the default values corresponding to a Mica2 mote in a typical environment (namely, path loss exponent = 4.7; shadowing standard deviation = 3.2; non coherent frequency shift keying; Manchester encoding; output power = -7.0dBm; noise floor = -105.0dBm; preamble length = 2; frame length = 50). The number of nodes is varied from 15 to 40 in steps of 5. All the nodes are deployed within a $12 \times 12m^2$(square meters) terrain. The source and destination nodes are fixed at location $(0, 0)$ and $(12, 12)$ respectively. We use the inverse of link PRR (Packet Reception Rate) as the link cost as this represents the expected number of transmission on the link if ARQ is used with constant transmit power setting. We use two models to simulate the node reliability, called the correlated model and uncorrelated model. In the correlated model, we set up the relationship between the cost and the reliability. Only links with $PRR \geq 0.5$ are considered for counting the degree, and with this constraint, the degree of each node is calculated and normalized to $[0.1, 1]$ with a linear mapping to ensure that max *degree* maps to 1 and $degree = 1$ to 0.1. In the uncorrelated model, node reliability is generated independently uniformly and randomly in $[0, 1]$.

5.2 Results

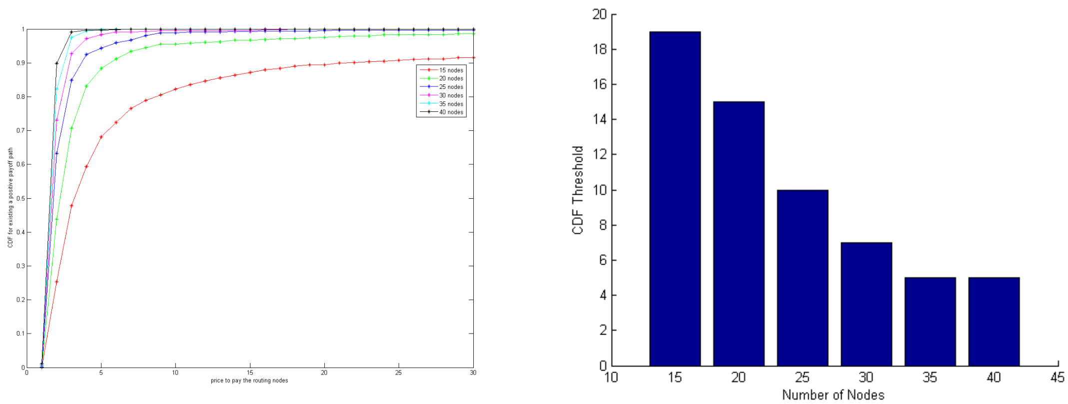
Figure 2(a) shows the probability that a positive payoff Nash equilibrium path exists as a function of the price offered by the source. For each curve, corresponding to a fixed number of nodes (fixed density), we see that the curve increases to a point where it is close to 1. This shows the existence of critical threshold prices (independent of the exact configuration) that ensure the existence of a Nash Equilibrium path with high probability. We also see that this price threshold decreases with the density, a trend that is concrete visualized in figure 2(b) which plots 90% price thresholds as a function of the node density. This trend is because with growing density there are more choices to pick the path from, and there are a greater number of high quality links which incur low transmission cost.

Figure 3(a) shows how the source utility (gain) varies as a function of the offered price. Initially there is an increase as there is a significant increase in the reliability of the paths that can be obtained with an increase in the price. However, beyond a point, offering higher prices is merely wasteful as it does not provide additional incentive for cooperation and the most reliable paths is already attained. Although the peak source utility varies with the node density, this figure suggests that the optimal price setting remains almost the same regardless of node density (there appears to be only a slow decrease within the range considered) — this bears further study. The peak source utility is plotted with respect to the node density also in figure 3(b). This shows that the peak utility improves with the number of nodes, which is also because of the diversity gains obtained with increasing density.

Figures 4 (a) and (b), and 5 (a) and (b) are the corresponding four sets of plots for the model where the node reliability values and link costs are uncorrelated. The only difference is that here the utility values are higher as the high degree nodes are no longer doomed to have poor reliability.

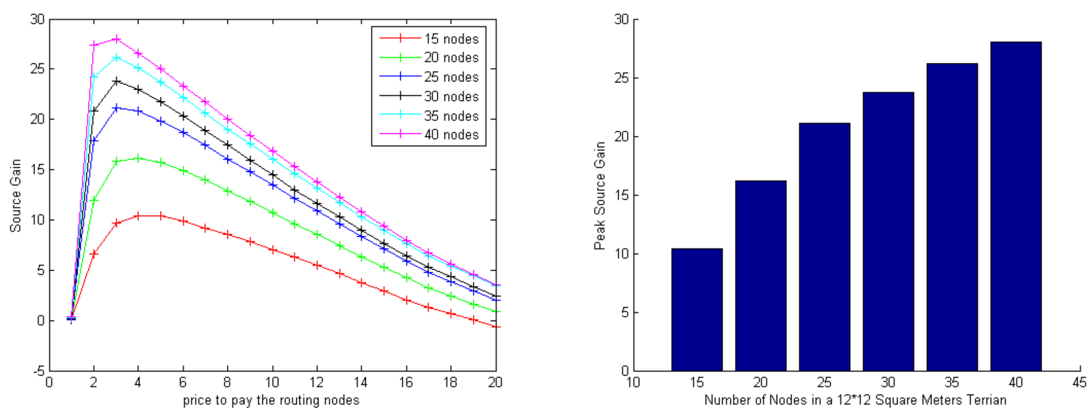
6 Conclusions

We have examined the problem of pricing cooperation in a network of unreliable nodes. Our problem formulation is similar to that presented by Kannan *et al.* [1, 3, 4]. Compared to much of the literature on inducing cooperation for routing, the key difference



(a) (b)

Figure 4: The probability that a positive payoff equilibrium path exists as a function of the price offered by the source and the 90% critical price threshold as a function of density (for uncorrelated reliability model)



(a) (b)

Figure 5: Source utility as a function of offered price, and Peak source utility as a function of density (for uncorrelated reliability model)

in this formulation is that for each node on the path there can be a tension between picking more reliable paths (which offers a greater expected payoff) and the transmission cost (which is different for different next-hop links, and hence for different path choices). However, contrary to the claims in [1, 3, 4], we are able to demonstrate a polynomial-time algorithm to compute the Nash Equilibrium for this problem.

In evaluating the impact of pricing, we find the existence of fixed critical price thresholds beyond which nearly all random configurations of a given density contain a positive payoff path that is in Nash equilibrium. Further, we find that there exists a density-dependent optimal price setting greater than this threshold value that maximizes the source utility. We find that increasing the density improves performance from the source's perspective as it reduces the critical price threshold and improves the peak source utility.

In future work, we are planning to provide analytical expressions to model the impact of pricing on the existence of the Nash equilibrium and on the source utility. This would allow us to make more concrete statements about how the critical price threshold and the optimal price settings vary with respect to different network parameters. We also plan to consider generalizing this work with respect to the payoff function.

References

[1] R. Kannan, S. Sarangi, S.S. Iyengar, "Sensor Centric Quality of Routing in Sensor Networks," IEEE Infocom, 2003.

[2] R. Kannan, S. Sarangi, S.S. Iyengar, "Game-Theoretic Models for Reliable Path-Length and Energy-Constrained Routing with Data Aggregation in Wireless Sensor Networks," *IEEE Journal on Selected Areas in Communications*, Vol. 22, No. 6, August 2004.

[3] R. Kannan, S. Sarangi, S.S. Iyengar, " Sensor-centric energy-constrained reliable query routing for wireless sensor networks", Journal of Parallel Distributed Computing, Vol. 64, pp. 839-852, 2004.

[4] R. Kannan, S. Sarangi, S.S. Iyengar, " A simple model for reliable query reporting in sensor networks Information Fusion," *Proceedings of the Fifth International Conference*, July 2002.

[5] Zong, Chen, Yang, Sprite: A Simple, Cheat-Proof, Credit-Based System for Mobile Ad-Hoc Networks", IEEE Infocom 2003.

[6] S. Marti, T.J. Giuli, K. Lai, and M. Baker. Mitigating Routing Misbehaviour in Mobile Ad Hoc Networks. In Proceedings of the Sixth Annual International Conference on Mobile Computing and Networking, MobiCom 2000.

[7] S. Buchegger, J. Y. Le Boudec, Nodes Bearing Grudges: Towards Routing Security, Fairness, and Robustness in Mobile Ad Hoc Networks, in 10th Euromicro Workshop on Parallel, Distributed and Network-based Processing, Canary Islands, Spain, January 2002.

[8] S. Buchegger and J. Y. Le Boudec. Performance Analysis of the CONFIDANT Protocol: Cooperation Of Nodes — Fairness In Dynamic Ad-hoc NeTworks. In Proceedings of IEEE/ACM Symposium on Mobile Ad Hoc Networking and Computing (MobiHOC), Lausanne, CH, June 2002

[9] Sorav Bansal, Mary Baker, "Observation-based Cooperation Enforcement in Ad Hoc Networks," Technical Report, cs/0307012, arxiv.org.

[10] A. Urpi, M. Bonuccelli, S. Giordano, "Modelling Cooperation in Mobile Ad Hoc Networks: a Formal Description of Selfishness", WiOpt Workshop: Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks INRIA Sophia-Antipolis, France, Mar. 2003.

[11] L. DaSilva and V. Srivastava, "Node Participation in Ad Hoc and Peer-to-Peer Networks: A Game-Theoretic Formulation", Workshop on Games and Emergent Behavior in Distributed Computing, 2004.

[12] M. Flegyhzi, L. Buttyn, and J.-P. Hubaux, Equilibrium Analysis of Packet Forwarding Strategies in Wireless Ad Hoc Networks – the Static Case, 8th International Conference on Personal Wireless Communications (PWC 2003), Venice, Italy, 23-25 September, 2003.

[13] M. Flegyhzi, J. Hubaux, L. Buttyn, "Nash Equilibria of Packet Forwarding Strategies in Wireless Ad Hoc Networks ", IEEE Transactions on Mobile Computing, Vol 5, No 5, pp 463-576, May 2006.

[14] E. Altman, A. A. Kherani, P. Michiardi, and R. Molva. "Non-cooperative Forwarding in Ad-hoc Networks", Technical Report INRIA Report No. RR-5116, 2004.

[15] O. Ileri, S. Mau, N. Mandayam, "Pricing for Enabling Forwarding inSelf-Configuring Ad Hoc Networks", In IEEE J. Sel. Areas Commun. Special Issue on Wireless Ad Hoc Networks, Jan. 2005

[16] L. Buttyan and J. P. Hubaux, "Stimulating Cooperation in Self-Organizing Mobile Ad Hoc Networks", ACM Journal for Mobile Networks (MONET), Vol. 8, No. 5, 2003.

[17] P. Nurmi, "Modelling routing in wireless ad hoc networks with dynamic Bayesian games", 1st IEEE International Conference on Sensor and Ad Hoc Communications and Networks (IEEE SECON) Santa Clara, Calif., Oct 2004

[18] V. Srinivasan and P. Nuggehalli and C. Chiasserini and R. Rao, "Cooperation in wireless ad hoc networks", In Proceedings of IEEE Infocom 2003.

[19] L. Anderegg, S. Eidenbenz, "Ad hoc-VCG: a truthful and cost-efficient routing protocol for mobile ad hoc networks with selfish agents", Proceedings of the 9th annual international conference on Mobile computing and networking, San Diego, 2003

[20] M. Jakobsson, J. Hubaux, and L. Buttyan, "A micropayment scheme encouraging collaboration in multi-hop cellular networks", in Proceedings of Financial Crypto 2003

[21] J. Crowcroft, R. Gibbens, F. Kelly and S. Ostring, "Modelling incentives for collaboration in mobile ad hoc networks", Performance Evaluation 57 (2004) 427-439.

[22] P. Michiardi and R. Molva, "CORE: A COllaborative REputation mechanism to enforce node cooperation in Mobile Ad Hoc Networks", IFIP - Communication and Multimedia Security Conference 2002

[23] N. Salem, L. Buttyn, J. Hubaux, M. Jakobsson, "A charging and rewarding scheme for packet forwarding in multi-hop cellular networks", In Proceedings of the 4th ACM international Symposium on Mobile Ad Hoc Networking and Computing ACM MobiHoc, New York, 2003

[24] M. Zuniga, B. Krishnamachari, Realistic Wireless Link Quality Model and Generator (to generate realistic static wireless ad-hoc/sensor network scenarios as graphs with links labeled with packet reception rates) [Version 1.1], December 2005. Available online at http://ceng.usc.edu/∼anrg/downloads.html.