Game-Theoretic Models for Reliable Path-Length and Energy-Constrained Routing With Data Aggregation in Wireless Sensor Networks

Rajgopal Kannan and S. Sitharama Iyengar, *Fellow, IEEE*

***Abstract*—Path length, path reliability, and sensor energy-consumption are three major constraints affecting routing in resource constrained, unreliable wireless sensor networks. By considering the implicit collaborative imperative for sensors to achieve overall network objectives subject to individual resource consumption, we develop a game-theoretic model of reliable, length and energy-constrained, sensor-centric information routing in sensor networks. We define two distinct payoff (benefit) functions and show that computing optimally reliable energy-constrained paths is *NP*-Hard under both models for arbitrary sensor networks. We then show that optimal length-constrained paths can be computed in polynomial time in a distributed manner (using $O(E)$ messages) for popular sensor network implementations using geographic routing. We also develop sensor-centric metrics called path weakness to measure the qualitative performance of different routing schemes and provide theoretical limits on the *inapproximability* of computing paths with bounded weakness. Heuristics for computing optimal paths in arbitrary sensor networks are described along with simulation results comparing performance with other routing algorithms.**

***Index Terms*—Energy-efficiency, network design, path weakness, reliable routing.**

I. Introduction

EMBEDDED sensor networks are massively distributed systems for sensing and *in situ* processing of spatially and temporally dense data. They consist of large numbers of autonomous, interconnected sensory nodes (sensors), which continuously sense and store attributes of locally occurring phenomena, [12] and can be deployed on a large scale in resource-limited and harsh environments such as seismic zones, ecological contamination sites, or battlefields [2]. Network tasks are executed by routing and cooperative processing of sensed information [12], [15].

The untethered and unattended nature of sensors in wireless sensor networks severely constrains the types of feasible routing algorithms. In data-centric information routing [3], [6], interest queries are disseminated through the sensor network for retrieving named data, i.e., data satisfying specific attributes. Further, data can be aggregated or combined at intersecting nodes along the routing tree to reduce data implosion. Packets must be forwarded along low-cost paths; minimizing overall energy consumption (aggregate path energy cost) is one possible routing metric [7], [11], [13]. However, such routing strategies may result in uneven energy depletion across sensor nodes and expedite network partition. Thus, it would seem preferable for sensors to forward packets based on local communication costs.

While *energy-efficiency* is an important parameter, several applications require the deployment of sensors in hazardous/hostile environments, where sensors can fail or be compromised by adversaries [17], [18] and, therefore, the *reliability* of a data transfer path from reporting to querying sensor(s) is a second critical metric. However, reliable routing paths obtained through forwarding decisions based on local energy choices may be quite long, leading to energy depletion at more sensors, while also increasing delay. Thus, *path length* is a third critical routing metric affecting both energy efficiency and sensor lifetime.

Note that while energy costs are local, path reliability and path length are global or network-wide metrics. Thus, routing strategies for the sensor network must be derived by optimizing these criteria simultaneously. In other words, sensors must cooperate to maximize network wide objectives (such as reporting queries via reliable short paths) without compromising their own survivability (as measured by their energy consumption). This paradigm can be labeled as sensor-centric [8]. Sensor-centric network components have to behave intelligently to find the right tradeoffs between efficient energy consumption and network-wide objectives. Obviously, network operability will be prolonged if a critically energy deficient node can survive longer by abstaining from a route rather than taking part for a small gain in overall reliability, latency or length.

In [15], the authors describe data-centric routing algorithms for sensor networks that take both energy constraints and quality-of-service considerations into account. Shah and Rabaey [14] show that the lowest energy path may not always be the optimal for long-term network connectivity. Their scheme probabilistically uses suboptimal paths to provide substantial gain. However, none of these protocols explicitly optimize route reliability and length in conjunction with minimizing communication costs.

Game-theory provides a natural framework to model the formation of multiply constrained routing paths by sensor-centric nodes. Specifically, sensors can be modeled as players in a routing game with appropriate strategies and utility functions (payoffs) that eventually lead to reliable-length-energy constrained routing paths/trees in the network. In this paper, we develop a simple game-theoretic model with different utility functions and analytically derive fundamental limits on the

Manuscript received July 15, 2003; revised February 1, 2004. This work was supported in part by the National Science Foundation (NSF) under Grant IIS-0312632 and Grant IIS-0329738 and in part by the Defense Advanced Research Projects Agency (DARPA) SensIT/AFRL under Grant F30602-02-1-0198.

The authors are with the Department of Computer Science, Louisiana State University, Baton Rouge, LA 70803 USA (e-mail: rkannan@bit.csc.lsu.edu).

Digital Object Identifier 10.1109/JSAC.2004.830937

performance of such routing strategies. We develop several sensor-centric metrics for measuring the quality (suboptimality) of routing paths. Simulation results demonstrate the potential of heuristic algorithms based on the game-theoretic approach for modeling cooperative sensor behavior. We summarize our main results as follows.

- We propose two different sensor-centric payoff functions for modeling the routing game resulting in the optimal reliable energy-constrained query routing tree (the RQR tree). Model II is more strategically constrained than model I and results in more reliable paths from sources to sink as compared with model I. Computing optimal trees under both models is *NP*-Hard.
- Rather than place explicit constraints on path length, we implicitly model this metric by considering reliable energy-constrained routing under a geographic routing regime. We show that optimal RQR paths under both payoff models can be easily found in polynomial time in such networks and the routing protocol can be implemented in a distributed manner.
- We propose sensor-centric metrics for evaluating the quality of routing paths/trees for data-aggregated routing in arbitrary sensor networks and derive inapproximability results on computing paths of bounded weakness. Simulation results comparing the weakness of paths obtained using a team-game-based routing heuristic called *fair-team-RQR* with some well known routing algorithms and identifying ranges of costs and probabilities in which they perform favorably are shown.

II. Game-Theoretic Reliable Energy-Constrained Routing Model

We first formally define the problem of RQR in a sensor network in game-theoretic terms and analyze the game subject to the additional constraint of path length in the next section. Given an unreliable energy-constrained network, how can we induce the formation of a maximally reliable data aggregation tree from reporting sensors (sources) to the query originating node (sink), where every sensor is "smart," i.e., it can tradeoff individual costs with network-wide benefits. This optimally reliable data aggregation tree (henceforth, the optimal RQR tree) will naturally be distinct from standard multicast trees, such as the Steiner tree [5] or shortest path trees, which minimize overall network costs and, therefore, cannot represent the outcome of self-interested sensors. The solution to this problem lies in designing a routing game with utility (payoff) functions, such that its Nash equilibrium [4] corresponds to the optimal RQR tree.

The proposed game-theoretic model for reliable energy-constrained routing consists of N sensors modeled as players denoted by the set $S = \{s_1, \ldots, s_i, s_j, \ldots, s_n\}$. We consider the following attributes of the system which form the components of the routing game. Note that while we describe these attributes using a static model, a dynamic extension would view them in terms of snapshots representing successive operational periods.

A. Costs

We model two types of costs in the network: communication costs and participation costs that model the cost to a sensor of deciding to participate in a given route.

1) Communication Costs: Communication between neighboring sensors in the network is implemented via the underlying medium access control (MAC) protocol. The energy cost of transmission is proportional to the distance between sensors [2]. We abstract the transmission link cost between neighboring sensors by $c_{ij} > 0$. Note that c_{ij} can refer to either per-bit (packet) costs or per-flow costs. While the former cost remains constant over an operational period (assuming immobile sensors), the flow costs are actually functions of the total amount of incoming flow to a sensor node and, thus, are affected by (and in turn affect the formation of) the routing topology. Also, for ease of presentation of our model, we assume that packet reception costs are zero, but can be incorporated in a straightforward manner.

2) Participation Costs: Our routing model should be rigorous enough to allow sensors to choose whether or not to participate in the routing process. By incorporating a participation cost to each sensor, we can analytically model situations where a sensor will collaborate in the query routing process only if the value of its information and the reliability of the reporting path gives it a positive payoff, thereby reducing unnecessary querying traffic. In other words, this cost is really an implicit benefit to all sensors not participating, since the cost of forwarding is eliminated. We abstract the participation cost at sensor s_i by

$$PC_i = h(B_i, F_i, T_i).$$

PC_i is modeled as a function h of events affecting the lifetime of the sensor, such as the remaining battery life B_i, the current traffic flow through the node F_i and the amount of processing power currently being consumed P_i. A sensor that chooses not to participate in any routing traffic (perhaps a sensor with extremely low-energy levels relative to its neighbors) can then turn itself off for a certain period to conserve energy.[1]

B. Strategies

Each node's strategy is a binary vector $l_i = (l_{i1}, l_{i2}, \ldots, l_{ii-1}, l_{ii+1}, \ldots, l_{in})$, where $l_{ij} = 1$ ($l_{ij} = 0$) represents sensor s_i's choice of sending/not sending a data packet to sensor s_j. Since a sensor typically relays a received data packet to only one neighbor, we assume that a node forms only one link for a given source and destination pair of leader nodes. In general, a sensor node can be modeled as having a mixed strategy [4], i.e., the l_{ij}'s are chosen from some probability distribution. However, in this paper, we restrict the strategy space of sensors to only pure strategies. Furthermore, in order to eliminate some trivial equilibria (such as all paths with no short-circuits, the empty network, etc.), each sensor's strategy is constrained to be nonempty and strategies resulting in a node linking to its ancestors (i.e., routing loops) are disallowed. Consequently, the strategy space of each sensor s_i is such that $\text{Prob.}\,[l_{ij} = 1] = 1$ for exactly one sensor s_j and $\text{Prob.}\,[l_{ij} = 1] = 0$ for all other sensors, such that no routing loops are formed. Under these assumptions each

[1]Here, we do not consider the specific protocol required to implement this participation mechanism (such as [1]). Our objective is to consider routing implications of this abstraction of individual sensor self-interest.

meaningful strategy profile $l = (l_1, \ldots, l_n)$ becomes a reverse tree $\mathcal{T}$, rooted at the sink s_q.

C. Benefits

Next, we abstract the benefits to a sensor for participating in the routing game.

1) Path Reliability: Since we wish to model reliable energy-constrained routing, the reliability of the realized routing path is a benefit to the sensors participating in it. We model path reliability using sensor failure probabilities. We assume that node s_i can fail with a probability $(1 - p_i) \in [0, 1)$. We make no assumptions about correlations in these probabilities, since the model primarily requires the values of partial path reliability, which we assume can be obtained. As before, while we assume static failure probabilities in developing our model, a dynamic extension would view the network in terms of failure probability snapshots in successive operational periods. Also, for simplicity, we assume that the sink node s_q never fails.

2) Information Value: Under the data-centric paradigm a query is sent from the sink node $s_q = s_n$ to the nodes in S. The query may match the attributes of data stored at each s_i to varying degrees. This data has to be reported back to s_q and aggregated along the way, if feasible. Information is routed to s_q through an optimally chosen set (via the routing game) $S' \subseteq S$ of intermediate nodes who form neighbor communication links. Our model should select data transfer paths based on the *importance* of the data being reported. For example, popular data items representing successful query matches must be treated differently and routed over more reliable paths even at higher costs, as the penalty for nondelivery is more severe. We abstract this idea of information retrieval by attaching a value $v_i \in \Re$ to the data retrieved from each sensor s_i, $1 \leq i < n$, ($v_i = 0$ for nodes whose sensor data does not satisfy the specified attributes of the query).

Note that since we are modeling self-interested sensors, we should account for nodes with valuable information but selfish behavior, i.e., nodes saving energy by deliberately not participating in the routing. For example, this could include compromized sensors which are suppressing information. One way to stimulate such nodes is via a punishment mechanism that values future information coming from a node propoprtional to the number of previous routes it participated in.

3) Benefit Functions: Sensors (players) in the routing game get benefits by making appropriate strategy choices. We can induce collaborative behavior to achieve a joint goal (reliability) among sensors within a noncooperative game by defining network-wide or shared benefits. Consider a strategy profile $l = (l_i, l_{-i})$ resulting in a tree $\mathcal{T}$ rooted at s_q, where l_{-i} denotes the strategy chosen by all the other players except player i. Since the network is unreliable and every sensor that receives data has an incentive in its reaching s_q, the benefit X_i to any sensor s_i on $\mathcal{T}$ must be a function of the path reliability from s_i onwards. Since the routing protocol includes data aggregation, X_i should also be a function of the expected value of information that can reach s_i. Hence, benefit $X_i = g_i(v_1, \ldots, v_{n-1})R_i$, where R_i denotes the path reliability from s_i onwards to s_q and $g_i(\cdot)$ is the value expectation function.

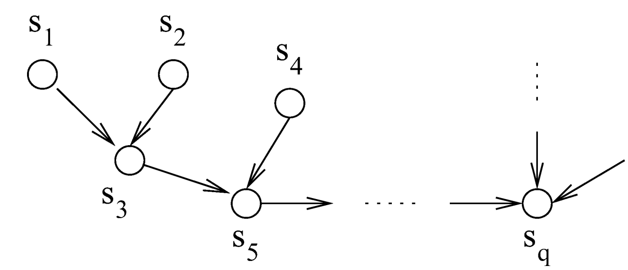


Fig. 1. Sensor benefits with data aggregation.

Consider the data-aggregation tree shown in Fig. 1. Let $\mathcal{V}_i = g_i(v_1, \ldots, v_{n-1})$ denote the value of the data at node i and $F(i)$ the set of its parents. We now describe two simple benefit models based on the form of $g_i()$.

Benefit Model I:

$$\mathcal{V}_i^I = v_i + \sum_{j \in F(i)} \mathcal{V}_j. \quad (1)$$

Model I captures the "memoryless" property of information transfer on a path, i.e., once information has reached a particular sensor its benefits in forwarding that information are not constrained by the choices of its ancestors and depend only on the survival probabilities of sensors from s_i onwards. Note, however, that costs may depend on the choices of ancestral sensors in the tree. Data aggregation is assumed to be additive in the figure.

Benefit Model II:

$$\mathcal{V}_i^{II} = v_i + \sum_{j \in F(i)} p_j \mathcal{V}_j. \quad (2)$$

For example, the benefit to sensor s_5 in the figure is $X_5^{II} = R_5(v_5 + p_1 p_3 v_1 + p_2 p_3 v_2 + p_3 v_3 + p_4 v_4)$. Unlike model I, here we model s_i as obtaining information from its parents only if they survive with the given probabilities. The value of information at s_i corresponds to the path reliability up to s_i. Ancestral actions reflected in this expected value also affect s_i's choice of potential next-hop neighbors, since s_i's benefits are partly dependent on the reliability of partial paths from its ancestors.

D. Payoffs

Let $l = (l_i, l_{-i})$ be any valid strategy profile resulting in a tree $\mathcal{T}$ rooted at s_q. The payoff at node s_i under $\mathcal{T}$ can be written as

$$\Pi_i(l) = \begin{cases} X_i - (c_{ij} + CP_i), & \text{if } s_i \in \mathcal{T} \\ 0, & \text{otherwise} \end{cases}.$$

Definition 1: A strategy l_i is said to be a best response of player i to l_{-i} if

$$0 \leq \Pi_i(l_i', l_{-i}) \leq \Pi_i(l_i, l_{-i}) \text{ for all } l_i' \in \mathcal{L}_i.$$

Let $BR_i(l_{-i})$ denote the set of player i's best response to l_{-i}. A strategy profile $l = (l_1, \ldots, l_n)$ is said to be an optimal RQR tree $\mathcal{T}$ if $l_i \in BR_i(l_{-i})$ for each s_i, i.e., sensors are playing a Nash equilibrium [4]. In other words, the payoff to a node on the optimal tree is the highest possible, given optimal behavior by all other nodes. A node may get higher payoffs by selecting a different neighbor on another tree, however, it can only do so at the cost of suboptimal behavior by (i.e., reduced payoffs to) some other node(s). The above features of our game-theoretic model allow sensors to rationally decide by computing best responses whether or not to participate in routing data of a given significance. Thus, link formation in the network occurs by a process of simultaneous reasoning at each node, leading to a path from each s_i with nonzero value v_i to s_q. It can be shown for this particular game that sequential reasoning by nodes in order of selection will also produce exactly the same equilibrium paths.

Note that under the definitions above, there may be a continuum of Nash equilibria corresponding to different optimal trees. Equilibria corresponding to more reliable paths are more desirable and the system should be made to converge to such points. When choosing between strategies (paths) with equal payoffs, nodes should always select edges leading to higher path reliability. In this context, the information value parameter has a significant impact on the number of equilibria/reliability of these trees. Higher information values will bias equilibrium points toward more reliable trees. For a simple example, consider equilibrium paths from a single source with value v_r to the sink. If there are two equilibrium paths, with reliabilities R_1 and R_2, where $R_1 > R_2$, increasing the value of v_r will proportionately increase the payoff from the R_1 path more than the R_2 path, thereby removing the latter path as an equilibrium point. Note that the particular benefit model also has a significant impact on the number of equilibria and their reliabilities. We can state the following.

Observation 1: Benefit model I induces more reliable equilibrium paths from source to destination compared with model II.

Clearly, model II is more strategically constrained than model I since all nodes on an equilibrium path share the same reliability benefit. Downstream nodes under model I can choose more reliable paths over edges that would be infeasible under model II. The reliability benefit in model II, (i.e., partial path reliabilities from the given node onwards) are *decreased* by the expected value factor (i.e., partial path reliability up to the given node). Thus, model I makes more edges in the network feasible, and hence potentially fewer and more reliable equilibrium points.

Given our assumption of additive data aggregation, many of the results that hold for reliable energy-constrained routing from a single source to the sink (i.e., RQR paths) also hold for routing from multiple sources to sink (i.e., the RQR tree). Hence, in the next few sections, we present our results mainly in terms of single source-sink paths and when necessary the result is stated in terms of trees.

III. Optimal RQR Computation in Arbitrary Sensor Networks

We first analyze the complexity of computing the optimally reliable data aggregation path (the RQR path) and tree (the RQR tree) under both payoff models in arbitrary sensor networks. In the next section, we consider some popular implementations of sensor-net architectures and show that the RQR computation is tractable and can in fact be easily computed in a distributed manner.

Result 1: Let $\mathcal{P}$ be the optimal RQR path for routing data of value v_r from a single reporting sensor s_r to the sink node s_q in a sensor network G, where $v_i = 0\ \forall i \neq r$. Computing $\mathcal{P}$ is *NP*-Hard under benefit models I and II.

The proof for both models follows by reduction from the Hamiltonian path problem [5]. For details of model II, please see [9].

Corollary 1: Given an arbitrary sensor network G with sensor success probabilities P, costs C, and data of value $v_i \geq 0$ to be routed from each sensor s_i to the sink s_q, computing the optimally reliable data aggregation tree $\mathcal{T}$ (the RQR tree) is *NP*-Hard for both payoff models.

For arbitrary sensor networks, both the RQR-path and RQR-tree problems remain *NP*-Hard for the special case when nodes have equal success probabilities. However, the case when all edges have the same cost is much simpler.

Observation 2: For both benefit models, given $p_i \in (0,1]$ and $c_{ij} + CP_i = c$ for all ij, the most reliable tree $\mathcal{RT}$ is always optimal. For uniform p_i, the optimal RQR tree is also the one with least overall cost.

We now identify some sufficient conditions for $\mathcal{RT}$ to be optimal when the probabilities of node survival are nonuniform. Let s_i and s_{i+1} be subsequent nodes on the most reliable tree. Denote by R_i, the reliability of the most reliable path from s_i to s_q with R'_i being the reliability along any alternative path from s_i. Let $\Delta c_i = (c_{i,i+1} + CP_i) - (c_{ij} + CP_i)$, where s_j is any neighbor not on the optimal path and ΔR_i is defined similarly.

Proposition 1: Given G and $P(s_i) = p_i \in (0,1]$, tree $\mathcal{RT}$ will be optimal under payoff model I if

$$\frac{\Delta c_i}{\Delta R_i} < \mathcal{V}_i$$

for all s_i on $\mathcal{RT}$.

Proposition 2: Given G and $P(s_i) = p_i \in (0,1]$, tree $\mathcal{RT}$ will be optimal under payoff model II if

$$\frac{\Delta c_{i+1}}{\Delta c_i} < \frac{\Delta R_{i+1}}{\Delta R_i}$$

for all s_i and s_{i+1} on $\mathcal{RT}$.

For brevity, we do not include the proofs of the propositions.

IV. Optimal RQR Computation in Geographically Routed Sensor Networks

Thus far, we have modeled reliable energy-constrained routing. However, energy efficiency and sensor lifetime are also affected by the length of routing paths since longer paths result in energy consumption at more sensors. Reliable query routing must, therefore, be addressed in terms of sensor-centric energy efficiency, as well as path length. We consider the RQR problem for sensor networks in which sensors are restricted to following a **geographic routing** regime. Geographically routed sensor networks are a popular implementation of sensor-net architectures [16]. The strategy space of each sensor in the geographically routed RQR game includes only those neighbors closer to the destination than itself. Routing paths under this regime are, thus implicitly length-constrained. For each sensor, the set of downstream neighbor nodes to a given destination can be found using protocols such as GFG [19] and greedy perimeter stateless routing (GPSR) [10].

Let G be an arbitrary sensor network following geographic routing with sensor success probabilities P, communication energy costs C, and data of value v_r to be routed from a single reporting sensor s_r to the sink node s_q, where $v_i = 0\ \forall i \neq r$. We assume static/fixed communication energy costs and no participation costs. While the RQR problem is *NP*-Hard for general sensor networks, we show that it becomes surprisingly easy when we add the additional constraint of path-length.

Lemma 1: Let $\mathcal{L}_i$ be the *longest* geographically routed path from s_i to s_q in G. Then, s_i can determine its optimal RQR neighbor under both benefit models in $|\mathcal{L}_i|$ steps.

Proof: We first note the following simple observation. In a geographically routed network, all feasible routing paths from s_r to any node s_i and from s_i to the sink s_q intersect only at s_i. If any other such node existed, it would have to be geographically closer than s_i to both s_r (since it is on a feasible path from s_r to s_i), as well as s_q (since it is on a feasible path from s_i to s_q), which is impossible.

Let $R(\mathcal{P}_i(v_i))$ represent the reliability of the optimal RQR path $\mathcal{P}_i$ from s_i to s_q, transmitting information of value v_i. From the observation above, s_i merely needs to know optimal values to s_q from each of its downstream neighbors. Let D_i represent this set. Then, the optimal neighbor for s_i is

$$N^I_{\text{opt}} = \arg\max_{s_j \in D_i} \{v_r p_i R(\mathcal{P}_j(v_r)) - c_{ij}\} \tag{3}$$

for model I, since each node transmits information of value v_r, and

$$N^{II}_{opt}(v_i) = \arg\max_{s_j \in D_i} \{\mathcal{V}_i p_i R(\mathcal{P}_j(p_i v_i)) - c_{ij}\} \tag{4}$$

for model II, where $\mathcal{V}_i$ is the expected value of information received at s_i from a given upstream neighbor. The number of such values is proportional to the number of paths from s_r to s_i, which can be exponentially large. However, these values can be divided into disjoint, contiguous intervals in $(0\ldots v_r]$, which makes next-hop selection much easier.

The lemma can now be formally proved by induction. Consider node s_i whose longest path to the destination is of length one. Under payoff model I, its optimal choice is to link directly to s_q. Under payoff model II, it will link directly to s_q for all values $v_i : p_i p_q v_i > c_{iq}$. s_q is unreachable for smaller values of v_i. Hence, at node s_i the optimal choices are divided into tuples consisting of (two) value intervals and optimal path reliabilities corresponding to each interval. During the k^{th} step of the algorithm, all nodes with $|\mathcal{L}_i| = k$ follow the same reasoning, based on the optimal choices of downstream nodes in step $k-1$. In payoff model I, optimal next-hop choices are unique for each node. However, in model II, each node has multiple optimal neighbors, based on a division of the incoming information value into disjoint intervals in $(0\ldots v_r]$. As we show in the distributed algorithm, these intervals are polynomial in number and calculated at each node on the basis of intersections of value intervals and optimal reliabilities from its downstream neighbors. ■

A. Distributed Implementation of Length-Constrained RQR

Let $D_i = \{s_{i_1}, s_{i_2}, \ldots, s_{i_l}\}$ be the set of downstream next-hop neighbors of s_i. For each node s_{i_j} in this set, let the expected values of incoming information be divided into N_{i_j} disjoint consecutive intervals $I_1^{i_j}, I_2^{i_j}, \ldots, I_{N_{i_j}}^{i_j}$, where $\bigcup_t I_t^{i_j} = (0, v_r]$ ($N_{i_j} = 1$ for payoff model I). Let $B(I_t^{i_j})$ and $E(I_t^{i_j})$ denote the (open) left and (closed) right endpoints and let $R(I_t^{i_j})$ be the optimal path reliability from s_{i_j} onwards for information of expected value in the given interval $I_t^{i_j}$. When information of expected value v_i arrives at s_i and is forwarded, the expected value of information at s_{i_j} is $p_i v_i$ (under payoff model II). Therefore, each value interval at s_{i_j} corresponds to an equivalent "stretched" interval at s_i with left endpoint $B()/p_i$ and right endpoint $\max(v_r, E()/p_i)$. Henceforth, the notation $I_t^{i_j}$ refers to the stretched interval at s_i rather than the actual interval at s_{i_j}.

Let $\pi_i(i_j, v_i, I_t^{i_j})$ represent the payoff to sensor s_i on sending information of value $v_i \in I_t^{i_j}$ to downstream neighbor s_{i_j}. Note that the payoff function is continuous and increasing through the entire range of v_i (as v_i increases the payoff can only increase). We can, therefore, assume that all intervals give a positive payoff since intervals with negative or zero payoff can be identified and removed. The following lemma shows that the payoff optimality of two intersecting intervals at different neighbors s_{i_j} and s_{i_k} can be determined using a single fixed point.

Lemma 2: If $\pi_i(i_j, v_i, I_t^{i_j}) < \pi_i(i_k, v_i, I_u^{i_k})$ for $v_i = \text{Inf}[I_t^{i_j} \bigcap I_u^{i_k}]$, then $\pi_i(i_j, v_i, I_t^{i_j}) < \pi_i(i_k, v_i, I_u^{i_k})$ for all $v_i \in [I_t^{i_j} \bigcap I_u^{i_k}]$. If the two payoffs are equal at the fixed point, then $\pi_i(i_j, v_i, I_t^{i_j}) \leq \pi_i(i_k, v_i, I_u^{i_k})$ throughout the intersection iff $R(I_t^{i_j}) \leq R(I_u^{i_k})$.

The lemma follows by definition of the payoff function in (2). Thus, to compare two different intervals, we only need to evaluate their payoff at the smallest intersecting point.

The following distributed algorithm at each node enables computation of the optimal length-constrained RQR path. We assume that upstream and downstream neighbors of each node are known *a priori*. The output of the algorithm is the set of disjoint and contiguous information value intervals at s_i along with the reliability and next-hop neighbor on the optimal path from s_i to s_q for each interval. Once this information is computed at each node, it creates a packet labeled *OPT-PKT* containing tuples $\langle I_t^i, R(I_t^i)\rangle$, $1 \leq t \leq N_i$ and forward it to each of its upstream neighbors, i.e., *OPT-PKT* are sent in the reverse direction of data transfer. The algorithm maintains the interval with the current highest payoff and uses the increasing and continuous property of the payoff function to compute the next interval. $n(I)$ refers to the neighboring sensor corresponding to interval I. $P(I)$ is the payoff from interval I at its left endpoint except when comparing payoffs in two intervals, in which case it is calculated at the smallest intersecting point. Finally, $R(I)$ is the path reliability from s_i onwards for information value in I. $P(I)$ at left endpoints and $R(I)$ are calculated *a priori*.

```
ALGORITHM OPT-NEXT-NEIGHBOR
At each sensor s_i:
If Received(OPT-PKT) from all neighbors in
D_i Do
 1. Create sorted list L of left
    endpoints of all intervals (excluding
    endpoint 0)
 2. I ← (I|P(I) = max(P(I_1^{i_j}) ∀i_j ∈ D_i).
 3. B(I_1^i) ← 0;
 4. R(I_1^i) ← R(I);
 5. Next-Hop(I_1^i) ← n(I);
 6. m = 1;
 7. while L is nonempty Do
 8.  I = Extract-Min(L); /* Remove minimum
     element from head of list L */
 9. if (P(I) >= P(I_m^i)) Do
    /* Indicates end of current value
    interval */
 10.    m ← m + 1 ;
 11.    B(I_m^i) ← B(I);
 12.    R(I_m^i) ← R(I) ;
 13.    Next-Hop(I_m^i) ← n(I);
 14. end if /* else I can never be optimal
     so take no action. */
 15. end while
```

The algorithm begins when s_i receives *OPT-PKT* from all of its downstream neighbors. The running time of the algorithm is dominated by step 1 which merges $l = |D_i|$ sorted interval lists from each neighbor. Let $N_T = \sum_{j=1}^{l} N_{i_j}$ be the total number of intervals. Step 1 can be done in $O(N_T \log |D_i|)$ time. Step 2 finds the interval with the highest payoff among the beginning intervals of all the neighbors and takes $O(|D_i|)$ time. All other steps can be performed in $O(1)$ time. Hence, we have the following.

Result 2: The optimal length-constrained RQR path in a sensor network with geographic routing can be computed in a distributed manner using reverse directional flooding with $O(|E|)$ total messages for both benefit models, where E is the number of edges in the the sensor network. Optimal neighbors at each node can be found in $O(|D_i|)$ time for payoff model I and $O(N_T \log |D_i|)$ time for payoff model II.

For the rest of the paper, we focus on fundamental aspects of the RQR problem for sensor networks with arbitrary (nongeographic) routing.

V. Quality-of-Routing (QoR): Measuring Path Weakness

We now consider the following fundamental performance issue: How do we evaluate the suboptimality of routing paths in sensor networks.[2] Such a QoR metric is straightforward for traditional routing algorithms that optimize a single (end-to-end) attribute such as energy cost, reliability, or latency. However, in the game-theoretic context where reliable energy-constrained routes in the network are derived as the equilibrium of sensor strategies, a new sensor-centric metric is necessary for evaluating and comparing different suboptimal paths. For example, one path may yield high payoffs for sensor i with low payoffs for sensor j, while the exact opposite situation may prevail on another path. We now define several sensor-centric QoR metrics for evaluating arbitrary routing paths based on the idea of node "weakness." This route evaluation paradigm essentially quantifies the suboptimality of a node participating in a given route, i.e., how much a node would have gained by deviating from the current path to an optimal one.

Let $\mathcal{P}$ be any path from the source sensor s_r to the sink node s_q. Consider any node s_i on $\mathcal{P}$ with ancestors $\{s_r, \ldots, s_{i-1}\}$. Let $\hat{\mathcal{P}}_{iq}$ be the optimal RQR path for routing information of value $\mathcal{V}_i$ (i.e., the expected value under any benefit model) to s_q from s_i in the subgraph $G \backslash \{s_r, \ldots, s_{i-1}\}$, assuming such a path exists. Thus, $\hat{\mathcal{P}}_{iq}$ represents the best that node s_i can do, given the links already established by nodes $s_r, \ldots, s_{i-1}$ **and** assuming optimal behavior from nodes s_i onward, downstream. Define the *node weakness* of s_i in path $\mathcal{P}$ as

$$\Delta_i(\mathcal{P}) = \Pi_i(\hat{\mathcal{P}}_{iq}) - \Pi_i(\mathcal{P}).$$

$\Delta_i(\mathcal{P})$ represents the payoff deviation for s_i under the given strategy profile (path) $\mathcal{P}$. A positive node weakness represents the fact that $\mathcal{P}$ is suboptimal for s_i, while a negative one indicates that s_i is benefiting more from this path (at the expense of some other sensor). $\Pi_i(\hat{\mathcal{P}}_{iq}) = 0$ if no optimal path from s_i exists (for example, all of s_i's neighbors might have very high communication/participation costs and cannot participate in any path). Note that $\Pi_i(\mathcal{P})$ can take on any value. We now define the following metrics for evaluating the suboptimality of routing paths.

1) *Path Weakness*: $\overline{\Delta}(\mathcal{P}) = \max_i \Delta_i(\mathcal{P})$.

   $\overline{\Delta}(\mathcal{P})$ identifies the maximum degree to which a node on the current path can gain by making a different strategy choice. The weakness metric embodies the idea that a path is only as good as its weakest node and allows us to rank the "vulnerability" of different paths.

2) *Weakness Differential* : $\widetilde{\Delta}(\mathcal{P}) = \max_i \Delta_i(\mathcal{P}) - \min_i \Delta_i(\mathcal{P})$.

   While the path weakness metric highlights only the worst-off node, this describes the disparity between the worst-off node (the one most likely to deviate to a new strategy choice) and the best-off node, under the current outcome of the routing game $\mathcal{P}$. A small weakness differential value provides some indication of the fairness of the given path.

Observation 3: $\{\overline{\Delta}(\mathcal{P}), \widetilde{\Delta}(\mathcal{P})\} = 0$ if and only if $\mathcal{P}$ is the Nash equilibrium (optimal) path of the game and positive for all nonoptimal paths.

Thus, paths with low weakness and weakness differential values are closer to the optimal and, hence, preferable. Note that the two weakness metrics can be similarly defined for data-aggregation trees. Given a sensor on any tree $\mathcal{T}$, its weakness can be calculated as its payoff deviation from the optimal tree that would have been obtained, given the expected value at that

[2] We assume a single source and destination pair and, hence, focus on routing paths rather than trees.

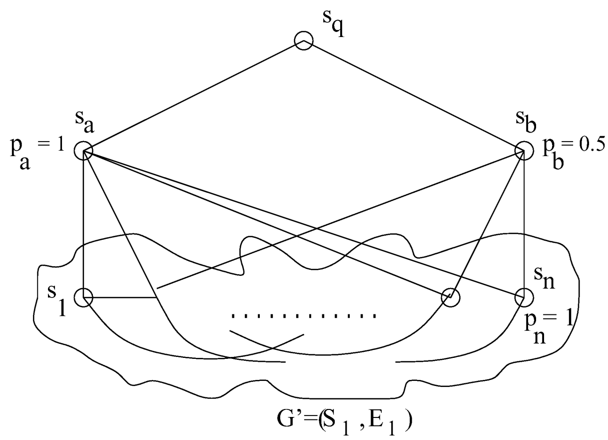


Fig. 2. Network illustrating inapproximabilty of path weakness metrics.

sensor along with the distribution of values in the remaining nodes in the graph.

A. Inapproximability of RQR-Path With Bounded Weakness

Next, we compute bounds for finding paths with low weakness. We will show that there exist networks where it is not easy to find paths of bounded weakness or differential by constructing a specific instance whose best suboptimal paths satisfy certain weakness characteristics.

Consider an arbitrary sensor network $G = (S, E)$ as shown in Fig. 2 with the following parameters. The vertex set S is the union of vertex set S_1 with nodes s_a, s_b and s_q. $G' = (S_1, E_1)$ is an arbitrary network, where $|S_1 = \{s_1, \ldots, s_n\}|$. s_1 contains information of value v_r to be routed to s_q. The edge set E for S is the union of disjoint edge sets E_1, $E_2 = \{(s_a, s_i)\} \bigcup \{(s_b, s_i)\}, \forall s_i \in S_1$, $E_3 = (s_a, s_q)$ and $E_4 = (s_b, s_q)$. Participation costs are set to zero. Communication costs are fixed and represented by the following edge costs-edges in E_2 cost ϵ, edge E_3 costs $v_r - \epsilon$ and edge E_3 costs $v_r/2 - \epsilon$, where $\epsilon < v_r/4$. The node success probabilities are $P(s_i) = 1$ for all $s_i \in S_1$, $P(s_a) = 1$ and $P(s_b) = 1/2$.

We now look at the optimal strategy choices for nodes in G on any path from s_r to s_q, under benefit model II. The analysis for benefit model I is very similar and, hence, omitted. Note that s_q is reachable only through s_a and s_b. Any path to s_q that does not contain s_b provides a benefit of v_r to all nodes on the path. All other paths provide a benefit of $v_r/2$ to all nodes on the path. Therefore, any path to s_q via s_a not involving s_b provides the maximum payoff of $v_r - \epsilon$ to nodes in S_1 on that path and a payoff of ϵ to s_a. s_a gets a higher payoff if it is an ancestor of s_b on any path. Thus, if s_a is visited before s_b, it will prefer to link to any nonvisited node in S_1 instead of linking directly to s_q. This path will eventually lead to s_q via s_b and provide a payoff of $v_r/2 - \epsilon$ to all nodes on that path except s_b and a payoff of ϵ to s_b. Note, however, that if s_b is visited first (before s_a), it can only link directly to s_q since all other paths to s_q via s_a yield a negative payoff for s_a and, hence, are suboptimal.

Consider the following four paths. $\mathcal{P}_1 = (s_1, s_a, s_q)$, $\mathcal{P}_2 = (s_1, s_a, s_i, s_b, s_q)$ for any $s_i \in S_1$, $\mathcal{P}_3 = (s_1, s_b, s_q)$, and $\mathcal{P}_4 = (s_1, \ldots, s_n, s_a, s_q)$ consisting of a Hamiltonian path $\mathcal{H} = (s_1, \ldots, s_n)$ in G' followed by s_a and s_q.

Assume that $\mathcal{H}$ exists in G'. If so, we can easily show the following node weakness values for each path:

$$\mathcal{P}_1 : \Delta_{s_1}(\mathcal{P}_1) = 0, \quad \Delta_{s_a}(\mathcal{P}_1) = \frac{v_r}{2} - 2\epsilon \tag{5}$$

$$\mathcal{P}_2 : \Delta_{s_1}(\mathcal{P}_2) = \frac{v_r}{2}, \quad \Delta_{s_a}(\mathcal{P}_2) = 0$$
$$\Delta_{s_i}(\mathcal{P}_2) = 0, \quad \Delta_{s_b}(\mathcal{P}_2) = 0 \tag{6}$$

$$\mathcal{P}_3 : \Delta_{s_1}(\mathcal{P}_3) = \frac{v_r}{2}, \quad \Delta_{s_b}(\mathcal{P}_3) = 0 \tag{7}$$

$$\mathcal{P}_4 : \Delta_{s_i}(\mathcal{P}_4) = 0 \forall i, \quad \Delta_{s_a}(\mathcal{P}_4) = 0. \tag{8}$$

We do not consider other paths that consist of visits to nodes in S_1 interleaved between visits to s_a and s_b or paths that visit s_b before s_a as they can be shown to have the same weakness characteristics as the above paths.

We can now conclude the following path weakness metrics:

$$\overline{\Delta}(\mathcal{P}_1) = \frac{v_r}{2} - 2\epsilon, \quad \overline{\Delta}(\mathcal{P}_2) = \frac{v_r}{2}, \quad \overline{\Delta}(\mathcal{P}_3) = \frac{v_r}{2} \tag{9}$$

$$\widetilde{\Delta}(\mathcal{P}_1) = \frac{v_r}{2} - 2\epsilon, \quad \widetilde{\Delta}(\mathcal{P}_2) = \frac{v_r}{2}, \quad \widetilde{\Delta}(\mathcal{P}_3) = \frac{v_r}{2}. \tag{10}$$

Finally, we have

$$\overline{\Delta}(\mathcal{P}_4) = 0 \quad \widetilde{\Delta}(\mathcal{P}_4) = 0. \tag{11}$$

Since G' is an arbitrary subgraph of G, the above result implies the existence of infinitely many graphs without any suboptimal paths of weakness or weakness differential bounded by $(v_r/2 - \epsilon)$. A similar analysis can be carried out for benefit model I. We have the following result, which is an improvement over [9].

Result 3: Under both benefit models I and II, there exists no polynomial time algorithm to compute approximately optimal RQR paths of weakness or differential weakness less than $(v_r/2 - \epsilon)$ unless $P = NP$.

Proof: Let $\mathcal{A}$ be an algorithm that outputs a path with weakness less than $v_r/2 - \epsilon$ in polynomial time. For the given ϵ, choose G with probabilities and costs as described above. We can then use $\mathcal{A}$ as a decision algorithm to solve the Hamiltonian path problem in G'. If a Hamiltonian path exists in G', it is the only path with weakness less than $v_r/2 - \epsilon$ in G and will, therefore, be output by $\mathcal{A}$. Algorithm $\mathcal{A}$ will return some other path in G (which can be verified as non-Hamiltonian in polynomial time) only if no Hamiltonian path exists in G'. Thus, $\mathcal{A}$ is a polynomial time decision algorithm for solving the Hamiltonian path problem. This is impossible unless $P = NP$. ■

B. Path Weakness Heuristics

Theorem 3 indicates the infeasibility of finding approximately optimal RQR paths of small weakness/differential in arbitrary sensor networks. Here, we present some easy to compute heuristics based on a fair-team version of the RQR game (called FTRQR), for finding approximate RQR paths. Simulation results presented in the next subsection verify that the FTRQR heuristic has low path weakness and compares favorably with other standard routing algorithms.

Define a "team" version of the RQR game as one in which all nodes on the path share the payoff of the worst-off node on it [9]. Rather than maximizing individual payoffs as in the original game, nodes in the team model compromise by selecting next-neighbors that maximize the shared least possible payoff. Formally, the payoffs to nodes in the network under strategy choice l leading to path $\mathcal{P}$ are as follows:

$$\Pi_i(l) = \begin{cases} R(\mathcal{P}) \left(\sum_i v_i \right) - \max_{(s_i,s_j)\in\mathcal{P}} (c_{ij} + CP_i), & \text{if } s_i \in \mathcal{P} \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

where v_i is the value of information at node s_i and $R(\mathcal{P})$ is the reliability of path $\mathcal{P}$ from s_r to s_q formed under strategy choice l. The Nash equilibrium of this team game is the path from source to destination containing the node with the maximum minimum cost-reliability tradeoff over all paths. In case of multiple equilibria, the path with highest reliability is selected.

While the above heuristic finds the path maximizing the payoff of the lowest payoff node, the disparity in individual payoffs (as defined in the original RQR game) between the best and worst-off nodes on the equilibrium path can be considerable. Thus, the node weakness of individual sensors on this path can also differ considerably and the path weakness, as well as the differential weakness might be high. Therefore, a heuristic that minimizes the differential path weakness (i.e., differences in individual node payoffs) of the equilibrium path will lead to: 1) more equitable sensor energy expenditures and 2) should potentially decrease the path weakness. However, such a heurstic might lead to less reliable paths. Since achieving energy fairness at the cost of reliability is against the overall routing objective, hence, the new equilibrium should also satisfy the original team notion of the RQR game. We, therefore, propose a composite heuristic labeled FTRQR, as shown in (13) at the bottom of the page.

The first component above addresses the team payoff aspect while the second component attempts to ensure that individual payoffs are as close to the team payoff as possible. The β parameter limits the impact of the payoff fairness criterion. Naturally, a weighted version of the two components is also possible.

The FTRQR heuristic bears some similarity to the standard bottleneck shortest path problem, which minimizes the cost of the longest edge on the path from the source to the destination node. The optimal FTRQR path can be interpreted as the bottleneck path to node s_q with the highest path reliability and lowest cost differential.

C. Experimental Results

In this section, we compare the path weakness characteristics of several standard routing algorithms along with the FTRQR team-game-based heuristic. We have used the following setup in our simulations: We consider routing from a single source containing information of value $v_r = 1$ to the sink on a 20-node random graph with 30% edge density, a uniform node survival probability, and random edge costs from a given parameter range. Edge costs are assumed static and node participation costs are set to zero. For each set of node success probabilities and edge costs, we evaluate the path weakness for routing paths under benefit model II from 15 source and destination pairs generated using: 1) the FTRQR heuristic; 2) the most reliable path (MRP); 3) the cheapest next-node path (CNP); and 4) the overall least-cost path (MCP). Equations (2) and (4) can be obtained using Djikstra's algorithm. The CNP is obtained by sequentially following the cheapest link out of each node that leads to the destination. For simplicity, whenever the algorithms produce paths with negative payoffs for some nodes, we set the path weakness value to one.

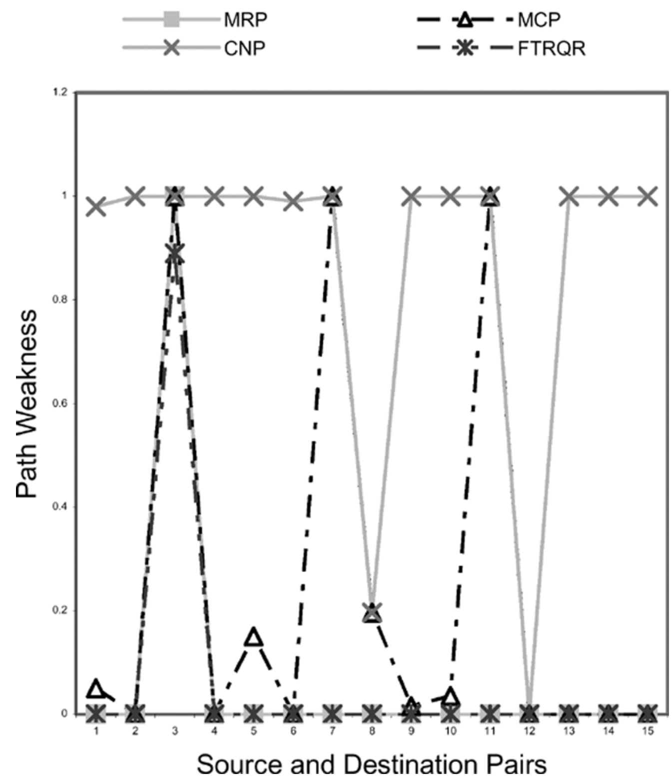


Fig. 3. $p = 0.5, c \leq 0.06$.

Analysis: Our simulation results are illustrated in Figs. 3–6. We are interested in finding ranges of costs and node success probabilities in which the different standard algorithms perform well. Initially, we model more unreliable and costly networks with low success probabilities and relatively high edge costs.

In Fig. 3, we keep the node success probability at 0.5 and the maximum edge cost at 0.06. This restricts the length of the optimal path since edge costs soon outweigh reliability benefits for nodes on long paths. In this case, MRP, the shortest path, always coincides with the optimal path despite the low node success

$$\Pi_i(l) = \begin{cases} \left(R(\mathcal{P}) \left(\sum_i v_i \right) - \max_{(s_i,s_j)\in\mathcal{P}} (c_{ij} + CP_i)\right) + \min\left(\beta, \frac{1}{\max_{(s_i,s_j)\in\mathcal{P}}(c_{ij}+CP_i) - \min_{(s_k,s_l)\in\mathcal{P}}(c_{kl}+CP_k)}\right), & \text{if } s_i \in \mathcal{P} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

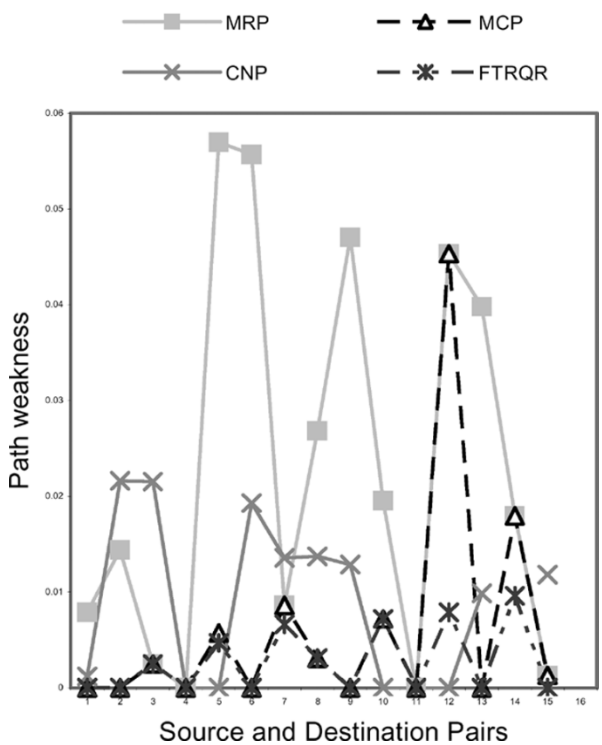


Fig. 4. $p = 0.995, c \leq 0.06$.

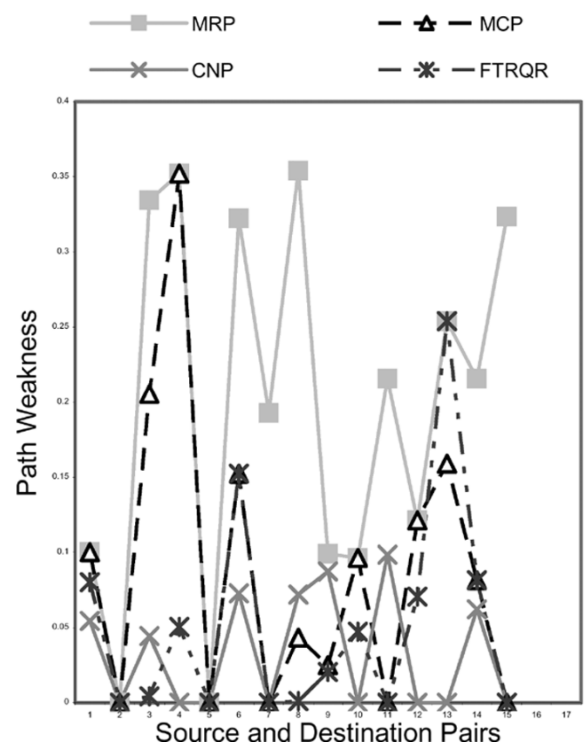


Fig. 5. $p = 0.98, c \leq 0.04$.

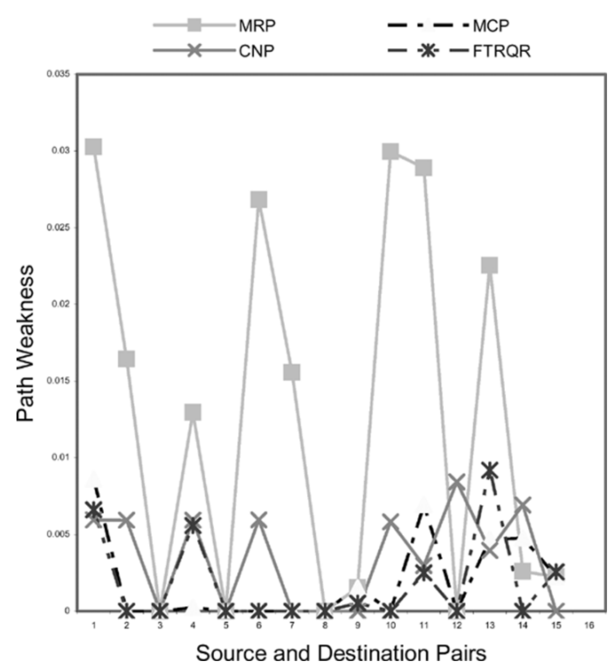


Fig. 6. $p = 0.999, c \leq 0.029$.

probability. FTRQR, because of its reliability component, also has very low weakness and coincides with the optimal in most cases. However, the cost-based algorithms, especially CNP have very high weakness since they result in much longer paths from source to destination. (Typically, CNP will result in the longest path since it minimizes individual node costs without regard to reliabilities).

In Fig. 4, we increase the node success probability dramatically to 0.995 keeping the maximum edge cost the same at 0.06. In this case, longer optimal paths are possible and routes based solely on maximizing reliability should not perform too well. This is clearly illustrated by the relatively higher path weakness values for MRP. Conversely, the CNP metric now (as compared with Fig. 3) has much lower weakness. Since nodes are more reliable now, the longer paths generated by CNP are not too suboptimal. However, FTRQR outperforms CNP since it combines reliability, as well as cost to a limited extent. Note that the MCP heuristic also does surprisingly well, even though it is exclusively based on minimizing total edge cost. Minimizing total edge costs in many cases (with low-maximum edge costs) will yield *short paths* with low edge cost variation on the path. Since all nodes in our simulations are set to have the same success probabilities, the reliability of the MCP paths will be quite high along with low individual edge costs. Hence, MCP performs well. Note that this feature of high reliability with low costs is shared by the FTRQR heuristic and this is why both heuristics perform well. However, we suspect that when node probabilities are nonuniform, MCP will perform poorly since MCP paths are likely to have low reliabilities, whereas the FTRQR heuristic trades off reliability and costs and should have low weakness even in such cases.

In Fig. 5, we decrease both maximum edge costs and probabilities slightly. The path weakness of MCP increases slightly (lower node success probabilities lead to lower MCP path reliabilities). MCP is slightly outperformed by FTRQR which conforms to the above intuition.

Finally, in Fig. 6, we consider a highly reliable network with very low edge costs. Now, optimal paths can have longer lengths without sacrificing reliability. Therefore, CNP which tends to have a longer length, has lower path weakness now. MRP has higher path weakness due the presence of large number of paths (including low individual edge cost paths) with high reliabilities. The FTRQR heuristic, which trades off path reliability and cost differences performs well as expected.

Based on these simulations, in summary, we can state that the sensor-centric paradigm works best in highly reliable yet low cost networks. For unreliable networks, using the MRP heuristic is preferable. When success probabilities are uniform or within a very narrow range along with low maximum edge costs, MCP is a good heuristic. CNP rarely produces paths of comparatively low weakness. The FTRQR heuristic performs quite well in most cases and has low path weakness as it inherits the reliability characteristics of MRP in unreliable networks and that of the cost optimizing algorithms in higly reliable networks

VI. Conclusion

We have shown that game theory offers a promising framework for modeling reliable length-energy constrained routing in sensor networks. By modeling sensors as rational agents within a routing game, we can demonstrate the ability of sensors to cooperatively (globally) route packets subject to their own (local) energy constraints. Several payoff models and utility functions are possible, and we have illustrated just two of these possibilities. For each utility function, several Nash equilibria exist. An interesting and open issue is the stability of the network under dynamic routing scenarios. Specifically, how stable is the Nash equilibrium of the RQR game in a dynamic environment, where links and sensors fail periodically and will the system converge to a particular equilibrium. Another interesting problem is the efficiency and practicality of implementing optimal RQR protocols in hierarchical (clustered) sensor networks. Is it beneficial to compute optimal paths within each cluster for routing to gateway nodes (that handle intercluster routing).

While the optimal routing problem turns out to be computationally hard for arbitrary sensor networks, polynomial time solutions for the optimally reliable paths/trees are presented for geographically routed sensor networks. We present two metrics for evaluating the QoR paths labeled path weakness and show the inapproximability of finding paths of bounded weakness in arbitrary sensor networks. However, our experimental results show that standard routing mechanisms like most reliable or cheapest energy paths are usually good. Our game-theoretically oriented algorithm–FTRQR compares favorably to the other standard routing algorithms.

References

[1] A. Cerpa and D. Estrin, "Ascent: Adaptive self-configuring sensor network topologies," in *Proc. INFOCOM 2002*, New York, June 2002, pp. 1278–1287.

[2] I. F. Akyldiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: A survey," *Comput. Networks*, vol. 38, no. 4, pp. 393–422, Mar. 2002.

[3] B. Krishnamachari, D. Estrin, and S. Wicker, "Modeling data-centric routing in wireless sensor networks," presented at the Proc. INFOCOM 2002, New York, June 2002.

[4] D. Fudenberg and J. Tirole, *Game Theory*. Cambridge, MA: MIT Press, 1991.

[5] M. R. Garey and D. S. Johnson, *Computers and Intractability*. New York: Freeman, 1979.

[6] C. Intanagonwiwat, R. Govindan, and D. Estrin, "Directed diffusion: A scalable and robust communication paradigm for sensor networks," presented at the 6th Ann. Int. Conf. Mobile Computing Networks (MobiCom 2000), Boston, MA, Aug. 2000.

[7] D. B. Johnson and D. A. Maltz, "Dynamic source routing in ad hoc wireless sensor networks," in *Mobile Computing*. Norwell, MA: Kluwer, 1996.

[8] R. Kannan, S. Sarangi, S. S. Iyengar, and L. Ray, "Sensor-centric quality of routing in sensor networks," in *Proc. IEEE INFOCOM*, San Francisco, CA, Apr. 2003, pp. 692–701.

[9] R. Kannan, S. Sarangi, and S. S. Iyengar, "Sensor-centric reliable routing in sensor networks," *J. Parallel Distrib. Comput.*, Jan. 2004.

[10] B. Karp and H. T. Kung, "GPSR: Greedy perimeter stateless routing for wireless networks," in *Proc. ACM/IEEE MobiCom*, Boston, MA, Aug. 2000, pp. 243–254.

[11] C. Perkins and E. Royer, "Ad hoc on demand distance vector routing," in *Proc. 2nd IEEE Workshop Mobile Computer Systems Applications*, New Orleans, LA, Feb. 1999, pp. 90–100.

[12] G. Pottie, "Hierarchical information processing in distributed sensor networks," in *Proc. Int. Symp. Information Theory*, Aug. 1998, pp. 163–168.

[13] V. Rodoplu and T. H. Meng, "Minimum energy mobile wireless networks," *IEEE J. Select. Areas Commun.*, vol. 17, pp. 1333–1344, Aug. 1999.

[14] R. C. Shah and J. M. Rabaey, "Energy aware routing for low energy ad hoc sensor networks," in *Proc. IEEE Wireless Communications Networking Conf. (WCNC)*, Orlando, FL, Mar. 2002, pp. 350–355.

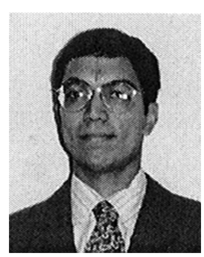
[15] K. Sohrabi, J. Gao, V. Ailawadhi, and G. Pottie, "Protocols for self-organization of a wireless sensor network," *IEEE Pers. Commun.*, pp. 16–27, Oct. 2000.

[16] Y. Yu, R. Govindan, and D. Estrin, "Geographical and Energy Aware Routing: A Recursive Data Dissemination Protocol for Wireless Sensor Networks," Comput. Sci. Dept., Univ. California at Los Angeles, Los Angeles, CA, Tech. Rep. UCLA/CSD-TR-01-0023, 2001.

[17] A. Wood and J. Stankovic, "Denial of service in sensor networks," *IEEE Comput.*, pp. 54–62, Oct. 2002.

[18] L. Zhou and Z. Haas, "Securing ad-hoc networks," *IEEE Network*, vol. 13, pp. 24–30, 1999.

[19] P. Bose, P. Morin, I. Stojmenovic, and J. Urrutia, "Routing with guaranteed delivery in ad hoc wireless networks," *ACM/Kluwer Wireless Networks*, vol. 7, no. 6, pp. 609–616, Nov. 2001.



Rajgopal Kannan received the B.Tech. degree in computer science and engineering from Indian Institute of Technology (IIT), Bombay, in 1991 and the Ph.D. degree in computer science from the University of Denver, Denver, CO, in 1996.

He is currently an Assistant Professor in the Computer Science Department, Louisiana State University, Baton Rouge. His areas of interest are in wireless sensor networks, data security, optical networks, routing and multicasting protocols, distributed systems, algorithms, and game-theory.

S. Sitharama Iyengar (M'88–SM'89–F'95) received the M.S. degree from the Indian Institute of Science, Bangalore, in 1970 and the Ph.D. degree from Mississippi State University, Mississippi State, in 1974.

He is the Chairman and Roy Paul Daniels Chaired Professor of Computer Science and is also Satish Dhawan Chaired Professor at the Indian Institute of Science. His publications include 13 books (authored or coauthored textbooks; Prentice-Hall, CRC Press, IEEE Computer Society Press, John Wiley & Sons, etc.) and over 280 research papers in refereed journals and conferences. He has served as a Guest Editor for the *Journal of Theoretical Computer Science* and the *Journal of Computer and Electrical Engineering*. He has been involved with research in high-performance algorithms, data structures, sensor fusion, data mining, and intelligent systems.

Dr. Iyengar was awarded the Distinguished Alumnus Award at the Indian Institute of Science in March 2003. He has served as an Associate Editor for the IEEE and as a Guest Editor for the IEEE Transactions on Knowledge and Data Engineering, the IEEE Transactions on Systems, Man, and Cybernetics, and the IEEE Transactions on Software Engineering, etc. He is also a Fellow of Association of Computing Machinery (ACM) and a Fellow of American Association of Advancement of Science (AAAS).