Increasing Connection Lifetimes through Dynamic Distribution of Budgeted Power

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***Abstract*—We present a new dynamic scheme which continuously redistributes a fixed power budget among mobile wireless nodes participating in a multi-hop wireless connection, with the objective of maximizing the expected lifetime of the connection. Our experimental simulations indicate that the proposed power budget distribution scheme yields a significant increase in connection lifetime. We quantify the sensitivity of the performance gains to various system parameters, including connection size, node density, power budget size, and mean node velocities. We then compare the efficacy of our scheme with two schemes: one that simply distributes the power budget uniformly, and one that distributes the power budget dynamically with the objective of minimizing end-to-end bit error rate (BER). In comparing the relative performance of the three schemes we obtain a qualitative assessment of the inherent oppositions and tradeoffs between the objectives of BER minimization and lifetime maximization.**

I. Introduction

Historically [1] reconciling the gap between power consumption and supply involved solving the following issues: (i) improving the power *efficiency* in the system; and (ii) preventing the system deconstruction due to un*fair* power usage. In their earlier work [2], [3] the authors proposed addressing these concerns by normalizing the measurement of relative “efficiency” and “fairness” using a model in which every connection is assigned a fixed power utilization budget. This assigned budget reflects the connection’s priority, or equivalently, the benefit that the system derives in maintaining the connection. In consumer MANETS, for example, this benefit might be based on financial incentives provided by a paying satisfied customer, while in military MANETs it could reflect the extent to which the connection is essential to achieving a positive outcome for some coordinated mission objective. In [4], the authors considered the opportunities afforded by such a model vis-a-vis minimizing connection bit error rate (BER), and presented a distributed scheme which minimized a connection’s end to end BER by continuously reapportioning its power budget among its constituent (static) nodes.

This work diverges and extends the earlier investigations of the authors [4] in two very significant ways: First, this paper considers *mobile* nodes instead of merely considering static snapshots of a dynamic network; secondly, our objective here is to leverage the ability to dynamically distribute a connection’s power budget towards *maximizing expected connection lifetime*, rather than towards minimizing connection BER. We will compare our proposed lifetime-maximizing scheme with the connection lifetimes enjoyed by the BER-minimizing power distribution scheme of [4], and in doing so obtain a sense of the extent to which the two objectives are in opposition.

II. Related Work

Efficient power management for MANETs has been investigated in prior research at several protocol layers (see e.g. [1]). As an objective, lifetime maximization has been interpreted in one of two ways: network lifetime maximization, and connection lifetime maximization.

Network Lifetime. The lifetime of a network is most frequently defined as the time interval for which the network is a connected graph. Broadly speaking, the network may partition (becoming disconnected) when one of two events occurs: (i) the autonomous movement of a node causes some of its incident link(s) to fail due to a shortage of transmission power, or (ii) some node exhausts its energy supply sufficiently so that some of its incident links fail. Most prior research on network lifetime attempts to delay the onset of these two types of events—the most frequent emphasis being on event type (ii), see e.g. [5], [6]—by extending the network routing protocol to make it energy-aware and using a route selection strategy that facilitates optimization with respect to the network’s lifetime.

Connection Lifetime. Somewhat analogously, a connection’s lifetime is typically taken to be the time interval during which all of the connection’s constituent links are operational. A link in a connection ceases to be operational when one of two events occurs: (a) the autonomous movement of one of the link’s endpoints causes it to fall out of transmission range of the other endpoint, or (b) one of the two endpoints exhausts its energy supply, causing the other endpoint fall out of transmission range. Most prior research on connection lifetime attempts to delay the onset of these two types of events—the most frequent emphasis being on events of type (a), see e.g. [7], [8], [9], [10], [11]. The main approach has been (as was the case in research on network lifetime) to extend the network routing protocol by making it energy-aware, and then to make route selection sensitive to connection lifetime maximization. In [7], [8], [9], [10], for example, the authors proposed new routing protocol extensions based on finding the path which probably has longest lifetime among many possible paths from source to destination. In these studies, the route selection process was based on the received signal strength at each of the nodes [7], [9], transmission range and the relative speed of the nodes [8], or recent changes in signal strength [11].

III. Problem Definition

The prior research described in the preceding section addresses those situations in which there is a very limited amount of energy available at each node, as is the case for example, in sensor networks or networks consisting of small mobile devices. Additionally, the strategies adopted in the prior research have centered on the routing layer, vis-a-vis energy-aware path selection. In contrast, we consider a model in which each connection's power requirements are modest compared to battery capacities, and where there are many connections which have been prioritized relative to each other by assigning each connection its own fixed *power budget* (i.e. a cumulative energy utilization rate). Our model better reflects the realities of battlefield settings in which the MANET nodes are unmanned autonomous vehicles [12], [13].

This work thus begins at the point where the research efforts on energy-aware routing end; we assume at the outset that the problem of route selection has been resolved e.g. by one of the schemes cited above. We describe a dynamic scheme that continuously redistributes the power budget assigned to a connection among its constituent nodes, with the objective of postponing events of type (a), thereby maximizing the connection's expected lifetime in the face of node mobility. We assume—as other similar investigations [14], [3], [2], [4] have—that each node is able to send with dynamically tunable transmission power. Each connection's power requirements are assumed to be modest relative to energy availability at the nodes, and connections are prioritized relative to one another by means of their power budgets. The proposed dynamic power distribution protocol is implemented on top of a routing protocol that is responsible for providing a multi-hop path between s and t, within total power budget constraints. We assume that node mobility is insignificant when compared to routing convergence times; the design of such energy-aware routing protocol is beyond the scope of this paper.

Fundamental Questions. Consider a single connection between a source node s and a destination node t, and assume that a transmission power budget P has been specified for this connection. The questions to be answered are:

Q1. How should P be distributed among intermediate nodes of the connection if the objective is to maximize the expected value of the connection lifetime?

Q2. How does such a power distribution scheme perform relative to a scheme which simply allocates power in a uniform static manner among the constituent nodes? How does it perform relative to a scheme which dynamically distributes power with the objective of minimizing end to end connection bit error rate?

IV. Network Model

We consider a wireless ad-hoc network consisting of N nodes equipped with omni-directional antennas that can dynamically adjust their transmission power. We model this network as a geometric graph $G = (V, E)$, where V is the set of nodes and E is the set of edges. Each node is assigned a unique ID i in $\{1, \ldots, |V|\}$, and node i can send data with a dynamically tunable transmission power.

Wireless propagation suffers severe attenuation [15]. If node i transmits with power $P_t(i)$, the power of the signal received by node j is given by $P_{rcv}(j) = \frac{P_t(i)}{c \times d_{ij}^{\alpha}}$, where d_{ij} is the distance between nodes i and j, and α, c are both constants, and usually $2 \leq \alpha \leq 4$ (See [15]). In order to correctly decode the signal at the receiver side, it is required that $P_{rcv}(j) \geqslant \beta_0 \times N_0$, where β_0 is the required signal to noise ratio (SNR) and N_0 is the strength of the ambient noise. We denote the minimum signal power at which node *i* is able to decode the received signal as $P_{min} = \beta_0 \times N_0$.

V. Power Distribution Schemes

The following sequence of observations are the intuitive foundation for the power distribution scheme we propose:

1) When a multi-hop connection fails, it does so because at least one of its constituent links has failed.
2) Consider the point in time T when the first link failure occurs. Suppose that one link L_1 of the connection has failed at T while another link L_2 still survives. Then the power budget must have been distributed suboptimally, since giving L_2's endpoints (infinitesimally) less power, and L_1's endpoints (infinitesimally) more power would have yielded a longer lifetime for the connection.
3) Thus, for connection lifetime to be maximized, power must be distributed in such a manner that at the point in time when the connection fails, *all* of its constituent links fail simultaneously.
4) If all nodes have the same sensitivity threshold P_{min} then item (3) implies that the power budget must be distributed in such a manner that the received signal power at each node in the connection is the same.
5) Suppose the connection has power budget P and the distance between nodes j and $j+1$ of the connection is d_j (for $j = 1, \ldots, N-1$). If node j transmits with power $P \cdot d_j^2 / \sum_{i=1}^{N-1} d_i^2$, then all nodes will receive the transmission from their upstream neighbor at the same power level, thus satisfying the conclusion of item (4). Additionally, the total power consumption attributable to the connection will be precisely P.

In what follows, we will refer to the dynamic power redistribution scheme deduced above as the *Sqr* scheme:

A. *Sqr Scheme*

Under this power distribution scheme, the power is allocated based on the square of the distance to the next hop along the path towards the destination node. Specifically, given a connection between nodes s and t with length $N-1$ hops and a total power budget P, each node j will be allocated

$$P_{sqr}(j) = P \cdot d_j^2 / \sum_{i=1}^{N-1} d_i^2,$$

where d_j is the distance from node j to node $j+1$ along the path. We compare the performance of *Sqr* with two existing well-known power distribution schemes:

B. Uniform Scheme

Given an N-node connection between nodes s and t having total power budget P, the *Uniform* power distribution scheme allocates power uniformly to each of the $N-1$ nodes (excluding the destination node) $P_{unif}(j) = \frac{P}{N-1}$.

C. MinBER Scheme

This power budget distribution protocol was originally described by the authors in [4]. The protocol operates on *all* (overlapping) consecutive triplets of nodes within the connection (s,t). Within each triplet, we denote the nodes as the upstream node, the central node, and the downstream node—this naming convention is illustrated in Figure 1.

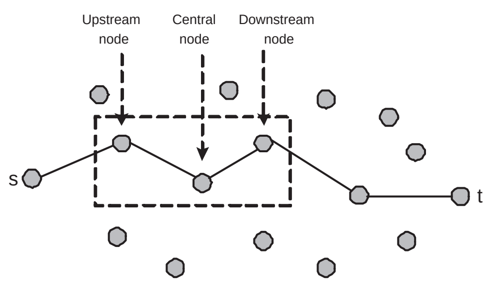

Fig. 1. Multi-hop path description

A node enters the protocol by simultaneously sending an Update message to its upstream and downstream neighbors. The Update message describes its present transmission strength. A node receiving an update uses its contents and the actual received signal strength to deduce an estimate of the distance to the sender of the Update. Thus each node (viewed in its central role) maintains estimates of distance to upstream and downstream nodes. When the central node receives an Update message informing it of the transmission power and (implicitly) distance to a neighbor, it determines the optimal redistribution of power between itself and the upstream node. This local optimization is computed using the analytic model of BER model presented in [4]. In effect the central node acts greedily to minimize the BER of the two hop sub-path from its upstream neighbor to its downstream neighbor. If the local optimization shows that a significant redistribution of power is required, and this redistribution will not cause the received signal strength to drop below P_{min} at any node, then the central node is able to draw power downstream or push power upstream. The power reallocation process is negotiated concurrently between all (overlapping) triplets of nodes via a distributed protocol. The protocol is said to "converge" when the total power exchanged drops below a specified threshold. Since we are interested in comparing the quality of power distribution decisions of various schemes, we assume that the *minBER* algorithm converges in timeframes significantly shorter than those involved in node mobility and routing; we denote the resulting power distribution at node j as $P_{BER}(j)$.

VI. Experimental Setup

Initial network design. In our simulations, we consider connections where the nodes were placed randomly according to the following inductive process: If node j is located at (x_j, y_j), then node $j+1$ is located at $(x_{j+1}, y_{j+1}) = (x_j + d_x, y_j + d_y)$ where d_x, d_y are uniformly distributed in the interval $[0, D]$. For most experiments (except when considering the effect of node density) we took $D = 100$ meters.

Mobility model. Nodes are allowed to move according to a Cartesian random walk mobility model [16]. Each node has five possible directions in which to move at each time step, of which one is selected uniformly at random: it may go north, south, east, or west with velocity v, or to stay at the current position until next time step.

Performance measures. Starting with an initial network, we generate a movement sequence for the nodes. Then we simulate this movement sequence under each of the three power distribution schemes and note the time at which the connection fails (i.e. one of the constituent links fails) for each of the schemes. We denote these times as T_{Unif}, T_{Sqr}, T_{BER} and compute the advantage or "gain" enjoyed by the *Sqr* scheme over the *Unif* scheme as $Gain_{Unif} = T_{Sqr}/T_{Unif}$, and the gain over the *minBER* scheme as $Gain_{BER} = T_{Sqr}/T_{BER}$. The preceding experiment is carried out repeatedly, in 10^4 independent trials, where each trial begins with a different random initial network and movement sequence. The aggregate performance metrics are computed as averages over 10^4 trials:

$$\begin{aligned} \text{Expected Gain over Uniform} &= E[T_{Sqr}/T_{Unif}] \\ \text{Expected Gain over minBER} &= E[T_{Sqr}/T_{BER}]. \end{aligned}$$

System and environmental parameters. We explored the impact of the following situational parameters on the above two performance metrics:

- *Number of nodes N:* We vary the number of nodes on the path ranging from few (5) to many (25) nodes.
- *Power budget P:* We consider connection power budgets ranging from small (2.0 Watts) to large (10.0 Watts).
- *Initial node density δ:* We vary node density in the initial network from sparse (0.15 nodes/m) to dense (0.4 nodes/m). This is achieved by taking $N = 500 * \delta$ and scaling the network geometry proportionally so that the initial network is bounded by the 500 meter square.
- *Mean node velocity v:* We consider velocity of the nodes ranging from slow (0.5 meters/sec; 1.1 miles/hr) to rapid (4.0 meters/sec; 9 miles/hr).

- *Signal attenuation exponent* α is taken as 2, appropriate to our connection distance scales in free space.
- P_{min}, the minimum signal power at which a receiver is able to decode a signal is taken as 10 mW.

VII. Simulation Results and Analysis

We conducted experiments to quantify the influence of the number of nodes N, connection power budget P, initial node density δ, and mean node velocity v, on the expected gain of *Sqr* over the *Uniform* and *minBER* schemes. The error bars on each graph below show the width of (plus/minus) one standard deviation from the expected values of the gains.

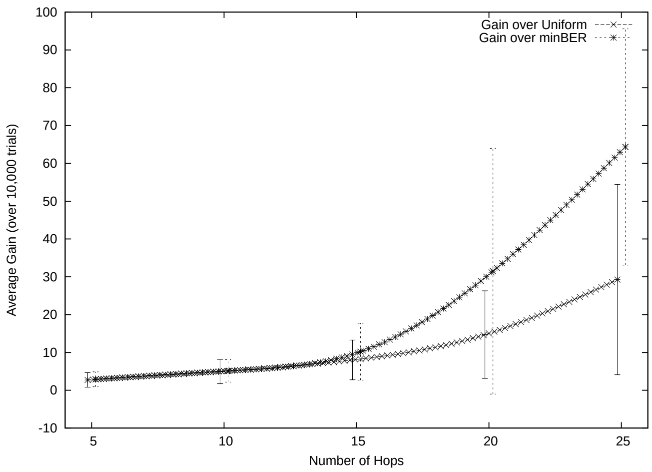

Fig. 2. The Influence of Number of Hops on Gain

Varying the connection size. In the first set of experiments, we varied the connection size from 5 to 25 nodes, while keeping all other variables fixed: the power budget (P) was fixed at 5.0W, the mean velocity of the nodes (v) was fixed at 1.0 m/sec, and the initial mean node density was one node every 50m. As can be seen in Figure 2, *Sqr* enjoys a linearly growing gain over both *Uniform* and *minBER* for small connections sizes (i.e. when $N < 15$), outperforming them both by a factor of 2.7 when $N = 5$, a factor of 4.9 when $N = 10$ and a factor of 8.5 when $N = 15$. As connection size grows beyond this threshold, the minBER scheme's power allocation decisions deviate significantly from the lifetime maximization scheme, and the rate at which the latter's gains increase begins to grow super-linearly. The reason for this divergence is explainable as follows. Since we are holding the connection's power budget constant while increasing N, when N becomes sufficiently large energy becomes scarce, and the power distribution which minimizes BER is markedly different from the power distribution which maximizes connection lifetime.

Varying the power budget. In the second set of experiments, we varied the connection's power budget from 2.0W to 10.0W, while keeping all other variables fixed: the number of nodes (N) was fixed at 10, the mean velocity of the nodes (v) was fixed at 1.0 m/sec, and the initial mean node density was one node every 50m. As can be seen in Figure 3, the

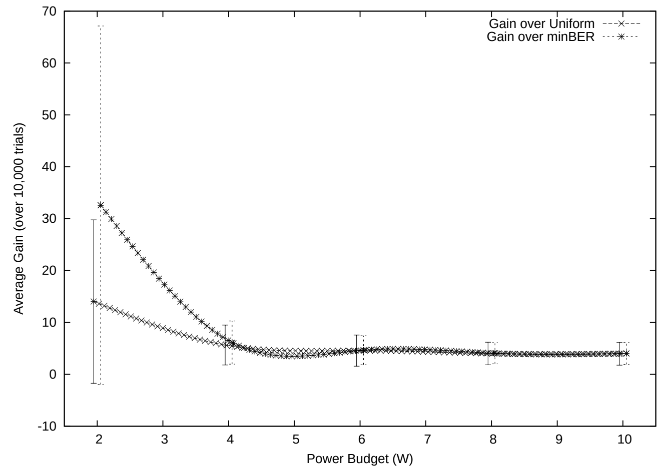

Fig. 3. The Influence of Power Budget on Gain

Sqr echeme enjoys a very significant (factor of 32) gain over *minBER* and factor of 14 gain over the *Uniform* scheme in low power budget settings (2.0W). As power budgets increase, the gain that *Sqr* enjoys over both schemes declines near-linearly. Once the power budget exceeds a threshold of 4.0W, any further increases of the power budget do not appear to separate *Sqr*'s factor of 3.9 advantage over *Uniform* and *minBER*.

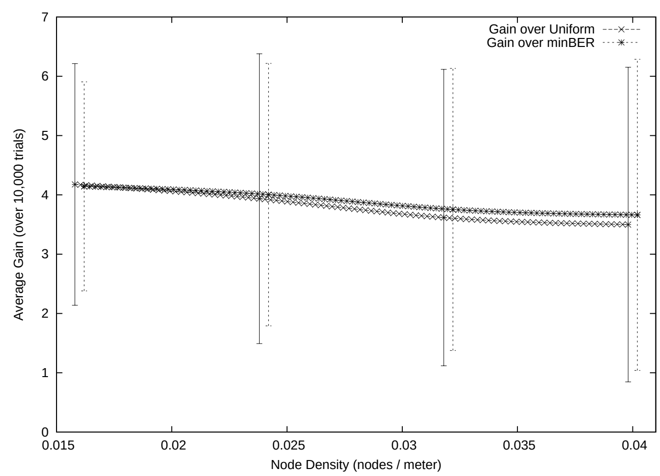

Fig. 4. The Influence of Node Density on Gain

Varying the node density. In the third set of experiments, we varied the node density from one node every 66m ($\delta = 0.15$ nodes/meter) to one node every 25m ($\delta = 0.40$ nodes/meter), while keeping all other variables fixed: the power budget (P) was fixed at 5.0W, the mean velocity of the nodes (v) was fixed at 1.0 m/sec. The number of nodes N was taken to be $500/\delta$, and the initial configuration was rescaled proportionately so that it was bounded by a 500m by 500m square. As can be seen in Figure 4, *Sqr* enjoys a significant gain in connection lifetime (a factor of 4.1) over both *Uniform* and *minBER*, although as node density increases, the gain is gradually reduced, becoming only a factor of 3.5 when the node density reaches $\delta = 0.4$ nodes per meter. Altering node density does not appear to separate *Sqr*'s advantage over *Uniform* from *Sqr*'s advantage over *minBER*.

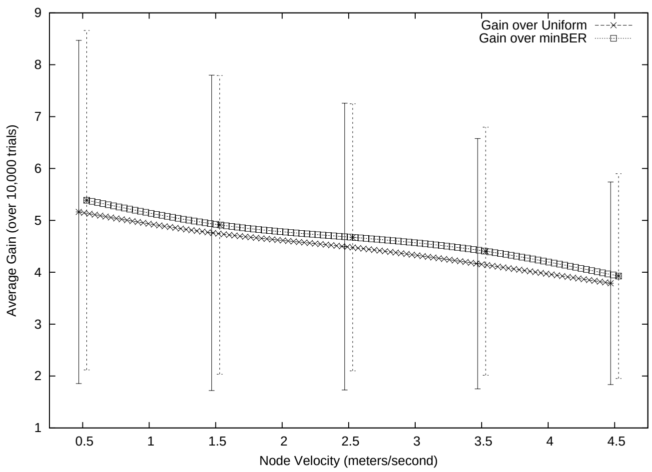

Fig. 5. The Influence of Node Velocity on Gain

Varying the node velocity. In the final set of experiments, we varied the mean node velocity from 0.5 meters/sec to 4.5 meters/sec, while keeping all other variables fixed: the power budget (P) was fixed at 5.0W, and the initial mean node density was one node every 50m. As can be seen in Figure 5, *Sqr* enjoys a significant factor of 5.2 gain in connection lifetime over both *Uniform* and *minBER*, although as node velocity increases, the gain is gradually reduced, becoming only a factor of 3.8 when the node velocity reaches 4.5 meters/sec. Altering node velocity does not appear to separate *Sqr*'s advantage over *Uniform* from *Sqr*'s advantage over *minBER*.

VIII. Conclusion

The proposed *Sqr* scheme is able to distribute a fixed power budget among the nodes of a connection, and yields significantly longer expected connection lifetimes relative to the uniform power budget distribution and the BER-minimizing power distribution schemes. The observed gains range from a factor of 3 to a factor of 30, depending on the particular values of system and environmental parameters. The expected gain is seen to be most sensitive to power budget and connection size, and relatively insensitive to initial node density and mean node velocity.

The objectives of BER minimization and lifetime maximization are most starkly in opposition in settings where the total power budget is low or, equivalently, where the size of the connection is large. It is in these settings that the distribution of power is most sensitive to the particular choice of objective, for in such settings, distributing power in a manner that achieves minimum end-to-end connection BER is very different from distributing power in a manner that seeks to maximize expected connection lifetime. The net impact of this tradeoff is that connections which are declared low priority (and hence assigned low power budgets) cannot expect to simultaneously optimize their power distributions with respect to both BER and expected lifetime, since the two criteria are seen to be in opposition. High-priority connections, on the other hand can "have their cake and eat it too", since with large power budgets, the relative advantage of *Sqr* over *minBER* (with respect to lifetime) is diminished.

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