Energy Balance in Wireless Networks Using Connection Segmentation and Range Control

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Abstract— **In a wireless network some nodes incur a disproportionate share of the packet forwarding burden than others: nodes lying toward the center tend to lie on more paths and therefore expend more energy in forwarding packets than other nodes, resulting in a shorter lifetime. While routes can be selected to alleviate this problem, we explore an entirely different and complementary approach by exploiting a wireless node's capability to adjust its transmission power. Each connection is partitioned into two segments, each of which either uses the regular network or direct transmission between the source and the destination. The relative durations of each segment are optimized to balance energy consumption across the network. This paper formulates an energy balance optimization problem in terms of the segmentation time, and an algorithm presented that reduces variance in energy consumption at the cost of a modest increase in average energy consumption. Algorithms are also presented for online and distributed solution of the optimization problem.**

I. Introduction

The general problem of addressing energy consumption in wireless ad hoc networks has received significant attention in recent years. Past research efforts include adapting the MAC layer [26], [31], network layer [30], [33], [34] and topology design [32], [25]. Among the many energy-related problems is the problem of fairness in energy consumption: because some nodes forward more packets than others, they are unfairly penalized for their important role in network operation. While route selection to balance energy [13], [31] is one approach that has been considered, route selection may be limited in some topologies (such as a star network). We consider a new, complementary approach that may be especially suited to wireless sensor networks in which long node lifetimes are an important requirement.

We take a market-driven approach to the problem of fairness in energy consumption by treating the forwarding function as a "public good" (in microeconomic terminology) to be shared by network nodes. We formulate optimization problems with two objective functions: minimizing the residual energy variance and maximizing the minimum residual node energy. Both of these objective functions are related to the lifetime of a network, since a node whose battery expires could cause network disconnection; to compound the impact, the node that expires first is likely to be the one carrying the most connections. We propose algorithms to solve the optimization problems that reduce variance (and therefore improve fairness) and increase minimum residual energy (and therefore lifetime) but at the cost of increasing the average energy. Our results show that substantial reductions in the objective function values are possible while incurring only a modest increase in average energy.

Our approach to controlling the balance of energy can be explained as follows. Intuitively, for the purpose of fairness, we would like long-duration connections and long-path connections to restrict their imposition of forwarding responsibilities on intermediate nodes. Similarly, we would like nodes that are geographically close to each other to communicate directly even if the routing algorithm prescribes a route through other nodes. Our prescription is intuitively simple: each connection partitioned into segments, whereby for some part of the connection's duration packets will be sent via the regular network route (incurring forwarding costs), and for the remainder, packets will be sent by direct transmission. To quantify this notion, we associate a real-valued control parameter with each connection i of duration t_i a parameter $x_i < t_i$. Direct transmission is used for a duration of length x_i whereas the network is used for the remainder $t_i - x_i$. Note that a less drastic (but less effective) approach in which direct transmission is used to route around a connection's hotspot for a duration x_i; we have addressed this issue in the full paper [29]. A key goal of this paper is to formulate a useful optimization problem involving the control variables x_i.

The partitioning of connections naturally invites questions about its practicality. One approach to partitioning is the following three-stage approach: a source node first uses direct transmission to achieve connection set-up; then packets are sent through the network in the second stage of duration $t_i - x_i$; finally, connection tear-down uses direct transmission again. The period immediately following the connection set up stage also uses direct transmission for a long enough period so that the overall duration of direct transmission is x_i. We refer to these three stages as *segments*, with analogy to the now-forgotten segmentation strategy for programs that once did not fit into main memory. This is not the only way to partition connections: other ways may prove more suitable. It is easy to see that the transfer of a large image or video clip can easily be divided into the three-stage approach. Clearly, for network applications with very small data requirements, such an approach might not be suitable. We anticipate that connection segmentation will also be useful in security: two nodes can execute a key exchange without involving intermediate nodes in the first stage of the connection.

Is there likely to be significant energy imbalance in most networks? A simple simulation result answers this question in the affirmative. We generated random topologies with an all-to-all communication pattern for each random topology, and estimated the "forwarding burden" on each node in the following way: the forwarding burden of a node is the number of con-

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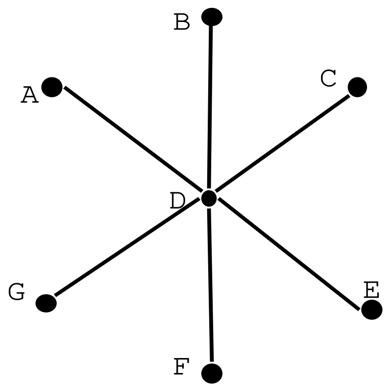


Fig. 1. Star Topology

nections that pass through the node. Thus, it is of interest to know the variance of this quantity for random topologies. We have observed that the coefficient of variation grows with network size. For particular network structures such as the star topology of Figure 1, the coefficient of variation can increase at the rate of $O(n)$ (where n is the number of nodes). Now consider the fact that the exponential distribution has a coefficient of variation equal to unity. Thus, in an absolute statistical sense, there is likely to be significant variation in energy consumption without mechanisms to enforce balance. This type of energy distribution has been observed by others as well [31].

Will direct transmission incur a significant increase in average energy even if the variance is reduced? Indeed, because signal power dissipates non-linearly (power loss is proportional to d^α, where d is the transmission distance and α is typically between 2 and 4), a straight-line path with multiple hops often uses less power than a direct transmission. Thus, there is some concern that enforcing fairness will raise the overall average energy beyond acceptability. For some networks, this may be indeed true; however, for randomly generated networks, our results show that average residual energy might increase only modestly while producing a considerable amount of decrease in variance and maximum energy consumed by a node. This is because the duration of the direct transmission segment is adjustable and therefore the optimization algorithms can select low values for long-distance connections. Furthermore, it is possible to define the problem so that the increase in average energy is constrained.

Finally, the possibility of changing transmission power during the connection suggests a violation of the sacred layering principle. The use of connection segmentation will call for changes to the protocol stack. We argue that such changes are perhaps justified in wireless sensor networks. Nodes in such a network are small enough to warrant a monolithic, compressed stack with a single layer.

The remainder of this paper is organized as follows. Section II presents an overview of related work. Section III contains our problem formulation while Section IV presents our offline solution, Section V presents the online variation of the solution, Section VI presents the distributed approach to solve the problem. Simulation results are given in Section VII before concluding with Section IX.

II. Related Work

Ad hoc networks have been a subject of much recent research. For example, several routing protocols and their analysis are presented in [1], [3], [2], [5], [4], [20], [8], [6]. Past research efforts have also studied various aspects of the energy consumption problem in wireless networks. In [14], [16] energy consumption for a wireless node has been studied. A power consumption model for adhoc networks has been proposed in [12]. The bulk of research in the area has focused on selecting routes that promote energy efficiency. Note that our work is complementary: when the network path is used instead of direct connection, energy efficient routes can be used that are computed using the above techniques. Many researchers have addressed the energy minimization problem at the routing layer level. In their seminal paper [30], Singh et.al describe power aware metrics which can be used in place of traditional metrics to compute routes in adhoc networks. Some approaches have been described in [11] and [9] that minimize the total power consumed on a path from source to destination and maximize lifetime or minimal residual power for a node in the network. An example of such networks are sensor networks with nodes having very limited resources and battery power [23].

Studies have shown that a lot of energy consumed by a wireless node is when it is *idle* because it has to process every received signal to detect an incoming packet. To alleviate this problem several *sleep-wakeup* mechanisms have been suggested. For example at MAC-layer these mechanisms are implemented in IEEE 802.11 [26] and PAMAS[31] . Some protocols suggested in [34], [36], [33], [19] reduce the energy consumption in the network by allowing only some of the nodes to be active at a time while other nodes remain in sleep mode. To distribute energy consumption the nodes take turns in remaining active. Another way of distributing energy has been suggested in [13] where the traffic is routed so that nodes spend energy in proportion to their residual energy. In [28] an approach is presented where nodes are awakened only when they are needed using a separate low duty channel. Some other methods for reducing energy consumption and maximizing lifetime of a node have also been studied. In [10] the use of power-aware applications has been suggested to reduce power consumption. In [7] optimal strategies for battery discharge have been presented to increase node lifetime. There are efforts to design complete power efficient protocol stacks[17].

In our paper we present an approach that exploits a wireless node's ability to control transmission power and hence control the transmission range. Range control has been a subject of research in the past. The use of output power control has been suggested in [35] for efficient frequency reuse. In [37] a power control loop for adhoc networks has been suggested. In [24] the objective is to maintain connectivity in a graph so that the maximum power level assigned to any node in the network is minimized. In [32] a distributed algorithm is proposed that ensures connectivity while reducing power consumption and interference at each node, and also ensuring power efficient paths between any two nodes. In [25] a distributed algorithm is described where all traffic is directed towards a master site to achieve a minimum power topology and ensure strong connectivity. In [27] the same range control approach has been taken to reduce energy consumption for multicasting in adhoc networks.

As mentioned earlier, we take a radically different, although complementary, approach to the problem of energy balance and network lifetime: we explore the possibility of segmenting connections as a way of creating yet another control option in attacking the general problem of energy conservation in wireless sensor networks.

III. Problem Formulation

We begin with a static offline formulation of the problem and later address the more practical online version and distribution implementation. Our network assumptions are not any different from those in past works on wireless ad hoc networks. We are given a set of wireless-capable nodes V and a set of connections J where each pair $(s_j, d_j) \in J$ specifies a source $s_j \in V$ and destination $d_j \in V$. A connection j is assumed to last t_j units of time. We will assume that some routing algorithm specifies the route used for each source-destination pair. For our simulations, we use the approach of finding the minimum common power-level required for network connectivity [18] and then computing the shortest path for each source-destination pair on the induced graph.

Let the initial energy of all the nodes be same and is denoted by E_{init}. Let the energy spent by a node $i \in V$ on a connection j be denoted by (E_{ij}) Then, the total energy spent by node i is

$$E_i = \sum_{j \in J} E_{ij}$$

the residual energy of the node after all the connections are over is

$$E_{res,i} = E_{init} - E_i$$

and the average residual node energy is

$$E_{avg} = \frac{1}{n} \sum_{i \in V} E_{res,i}$$

The energy variance is defined as

$$E_{var} = \frac{1}{n} \sum_{i \in V} (E_{res,i} - E_{avg})^2.$$

(An alternate definition would divide the sum by $n-1$.) Finally, the node that has the least residual energy has an energy level of

$$E_{min} = \min_{i \in V} E_{res,i}$$

The objective function we wish to minimize is the variance E_{var} and we will study its effect on minimum residual energy E_{min}.

Next, we will express the objective function in terms of our control variables. To do this, we will express each E_{ij} above in terms of the control variables $x_j, j \in J$. Consider a connection $(s_j, d_j) \in J$. Recall that our approach calls for using two different power levels during a connection. One power level is required for direction transmission from s_j to d_j. This power level is often (but not always) higher than the second power level which is prescribed by the routing algorithms for transmission through the network via neighbors of s_j.

Now, let the (real-valued) control variable x_j specify the amount of time spent in direct transmission where $0 \leq x_j \leq t_j$. Consider a node $i \in V$. Let P_j denote the power level required for direct transmission in connection j and let P denote the common power level prescribed by the routing algorithm. Also, let c denote the energy consumed by the receiving circuitry in the transceiver – as an approximation (since we are not focused on minimizing receive power), we take this as a constant across all nodes. Then, E_{ij}, the energy spent on connection j by node i can be expressed as:

$$E_{ij} = \begin{cases} P(t_j - x_j) + P_j x_j, & \text{if i is the source} \\ & \text{of connection j} \\ (P+c)(t_j - x_j), & \text{if i is intermediate node} \\ c t_j, & \text{if i is the destination} \\ 0, & \text{if i has no role in j} \end{cases}$$

Thus, by combining the above expression with the definitions of the objective functions (variance and minimum residual nodal energy), we can relate the control variables x_i to the objectives. To summarize, we have two objective functions (E_{var} and E_{min}). We will also present three different types of algorithms aiming to optimize these objective functions.

IV. Offline-Static algorithm

We now study the static problem in which the connection pattern is known in advance and the optimization problem is solved offline. Since our control variables are real-valued, we use an iterative gradient algorithm [21]. Let $x_j^{(k)}$ denote the value of control variable x_j after the k-th iteration and let $E_{var}(x^{(k)})$ denote the variance at the k-th iteration. Then,

$$x_{j,k+1} = x_{j,k} - \alpha \frac{\partial E_{var}(x^{(k)})}{\partial x_{j,k}}$$

where α is the stepsize. Note that the above iteration attempts to solve the variance minimization problem. Two inconvenient facts complicate the optimization problem. First, the variables x_j must satisfy the inequality constraints $0 \leq x_j \leq t_j$. Second, the objective function exhibits local minima To mitigate the problem of local minima, we use several different runs of the algorithm starting with different initial vectors $x^{(0)}$. The inequality constraints are handled as follows: an update to a variable $x_j^{(k)}$ in iteration k that results in violating the constraint is ignored in that iteration.

Note that the static optimization problem is not directly suited to scenarios in which connections arrive and depart in random patterns. However, the static approach is useful when communication patterns can be determined and enforced at prior to network deployment, or when periodic re-calculation of the variables is possible after periods of traffic estimation. Many applications for sensor networks fall into this category since sensors are programmed to engage in regularly scheduled rounds of communication. In these cases, the size of the data is known and therefore, the connection duration can be estimated ahead of time.

V. ONLINE ALGORITHM

In the online version [15] of the problem, when a connection j arrives the source node must decide the duration of the direct transmission time x_j to minimize the variance in the residual energies at the time of the connection arrival. Let $x_j^{(k)}$ denote the value of control variable x_j after the k-th iteration and let $E_{var}(x^{(k)})$ denote the variance at the k-th iteration. Then our modified gradient algorithm can be stated as follows:

1. Choose a sufficiently small real value step.
2. Find the gradient $\frac{dE_{var}(x^{(k)})}{dx_{j,k}}$
3. If gradient is approximately equal to zero then break
4. If the gradient has changed sign $step = \frac{step}{2}$
5. If gradient is greater than zero $x_{j,k+1} = x_{j,k} - step$
6. Else if gradient is less than zero $x_{j,k+1} = x_{j,k} + step$
7. Repeat steps 1-6.

To explain our algorithm for minimizing E_{var} we observe that if the gradient is positive we have to decrease x_j by some amount in order to reach minima . Similarly if gradient is negative we have to increase x_j . We change the value of x_j by a small quantity *step* in each iteration. If we find that the gradient has changed sign we infer that minima lies between $x_j - / + step$ and current value of x_j hence we reduce the value of *step*. After sufficient number of iterations we will either reach minima or be fairly close to it in which case the algorithm halts.

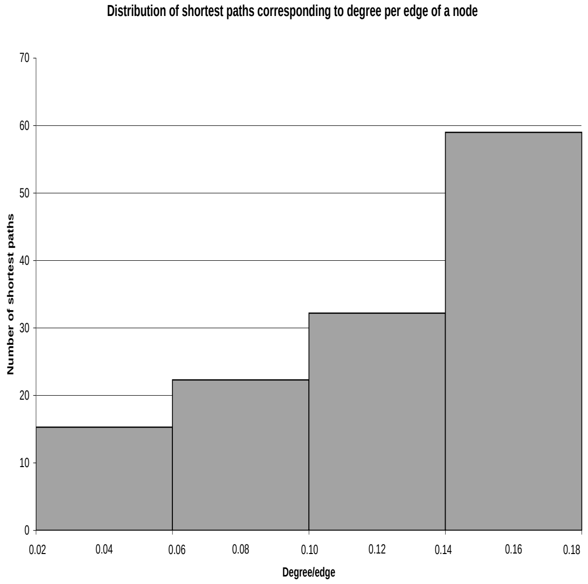
VI. DISTRIBUTED ALGORITHM

We now consider a distributed algorithm for the problem. In particular, we examine the possibility of designing an algorithm that uses only locally available information at each node. That is, a node decides the value x_j for those connections arriving at the node with no knowledge of connections at other nodes.

What local information could a node use in determining the segmentation? Intuitively, x_j should depend on the duration of the connection, the distance from source to destination, the likelihood that the node carries a high packet-forwarding burden and its current residual energy. Other factors might also play a role: the edge-density of the network, the number of hops from source to destination and the receive-only power of the node, for example.

To model the likelihood that a node carries high forwarding burden, we simply use the node's degree. Figure VI supports this idea. Here, we have drawn a histogram for a 20-node graph plotted on a $100 \times 100m$ grid. We construct all-to-all shortest paths on this graph. As the $(degree/edge)$ ratio increases on average, we see the number of shortest paths passing through a node increases.

The actual value of x_j will be difficult to model in terms of all the above parameters. Accordingly, as a heuristic we consider



the following approach:

$$x_j = \rho(1 - \frac{k}{E})(\frac{(n+1)(P+c)}{P_j})$$

where ρ is a scaling factor based on the residual energy of the source node E_{src}. Observe that the heuristic reduces the time for direct connection for a node with high degrees. The term $1-(\frac{k}{E})$ reduces as the degree of a node increases relative to the number of edges in the graph. Next, from the problem formulation, we see that direct transmission for one connection saves the total network energy by $(n+1)(P+c)x_j - P_j x_j$. Thus the ratio $\frac{(n+1)(P+c)}{P_j}$ is indicative of the energy that can be saved if direct transmission is used. Hence, if P_j is large compared to $(n+1)(P+c)$ the time of direct transmission should be lowered. Similarly, if $(n+1)(P+c)$ is large in comparison to P_j the direct transmission time should be increased. The role of ρ can be explained as follows. Let E_{init} denote the initial energy of a node then based on the value of $\frac{(E_{src}}{E_{init})}$ we can choose different values for ρ. For example if $\frac{(E_{src}}{E_{init})\leq 0.25}$ or the energy resources of a node are relatively low we may choose a small value (e.g., $\rho = 0.25$) to reduce the time of direct transmission.

VII. SIMULATION RESULTS

We evaluated the above algorithms using random topologies generated on a 100×100 grid. We assume that the power required for communication between any two nodes separated by a distance d varies as $Power = \gamma d^2 + \beta$ where γ and β are constants.

For simulation purposes power is measured in milliwatts and value of $\frac{\gamma=10mW}{m^2}$ while value of beta is $30mW$. The energy is reported in joules. Initially, the nodes are randomly placed on this grid. The following approach is used to construct network routes. A minimum spanning tree is constructed over the nodes. The length of the longest edge in this tree is taken to be the threshold distance T [18]. The power P required to transmit over this distance is the common transmit power assigned to all nodes when the network routes are used. For direct transmission, each source computes its power requirement separately. Note that a further optimization is possible in computing the network routes: each node can use the minimum power needed to transmit across the link that connects the node to the spanning tree. But this approach leads to a sparse topology and place an even heavier forwarding burden on some nodes. Now, the direct transmission approach is only used between nodes that are not neighbors in the network topology. Thus, neighboring nodes always use the constant power P in both the standard route approach and our approach.

Once the graph is constructed and minimal common power P determined, each node forms a neighbor set (all nodes which are less than distance T away). On this topology, we compute the shortest path between every source and destination to use as the network path.

In our simulations, we varied the number of randomly created connections (each of which is given a randomly generated connection duration). For each configuration we evaluated our algorithms on the mean, variance and minimum residual energy. In order to make the results comparable we show standard deviation instead of variance as there is a huge difference between the magnitudes of variance and other two metrics (i.e mean and minimum energy).

The following summarizes our results:

- Variance is reduced while minimum residual energy is increased substantially when we apply our optimizations.
- Average energy increases only slightly.
- The static offline approach yields the best results, as may be expected.
- The distributed algorithm performs better than the online algorithm.
- The objective function of minimizing variance is equivalent to increasing minimum residual energy to some extent.

In the figures the terms SDinit, Emaxinit and Eavginit denote the values of standard deviation, maximum energy consumed in the network and average energy respectively when no optimizations are applied. The terms SD, Emin and Eavg denote the corresponding values when the our algorithm is used.

In figures 2 and 3 we plot the standard deviation and the average energy and the minimum residual energy for the static offline optimization. We observe that deviation can be reduced by up to 54% , the minimum residual energy can be increased by 4 times while the average energy is decreased by atmost 2%.

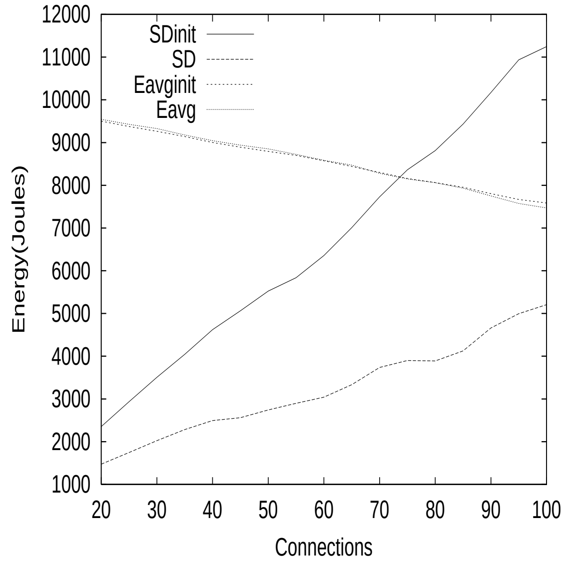


Fig. 2. Deviation and average energy on increasing connections for offline optimization

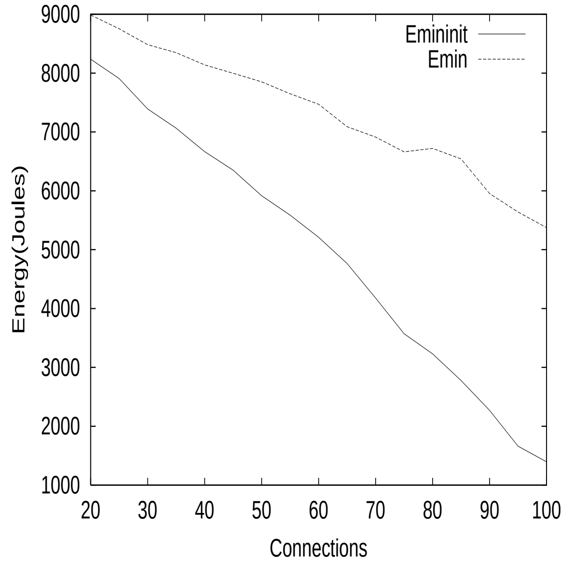


Fig. 3. Minimum Residual energy on increasing connections in static offline optimization

In figures 4 and 5 we plot the standard deviation and the average energy and the minimum residual energy for online variation. We observe that deviation can be reduced by up to 20%, the minimum residual energy can be increased by 70% while the average energy is decreased by atmost 1.5%.

In figures 6 and 7 we plot the standard deviation and the average energy and the minimum residual energy for the distributed algorithm. We observe that deviation can be reduced by up to 30%, the minimum residual energy can be increased 1.3 times while the average energy is decreased by atmost 3%.

VIII. Discussion

As must be clear now, our approach relies on the fact that intermediate nodes do not spend any energy on a connection's segment that is transmitted directly from source to destination. A node's transceiver can be turned off when the node is not being used and turned on when required and several such schemes aimed at conserving energy in ad hoc networks have been proposed previously both at the routing [33] and MAC layers [31], [26]. The power output and thus the transmission range of a transmitter can also be controlled dynamically.

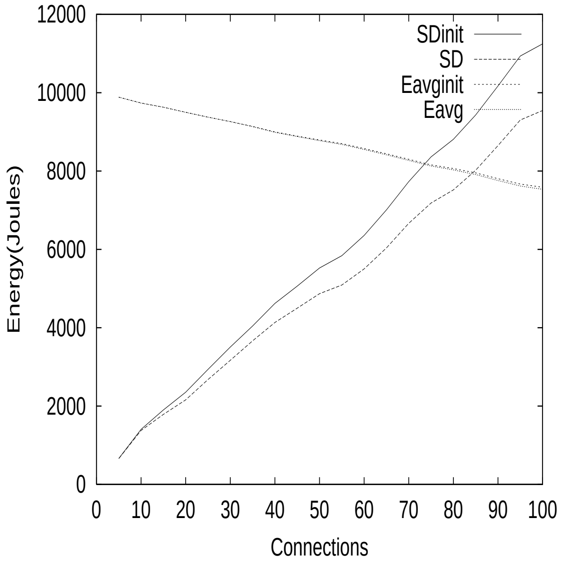


Fig. 4. Deviation and average energy on increasing connections for online algorithm

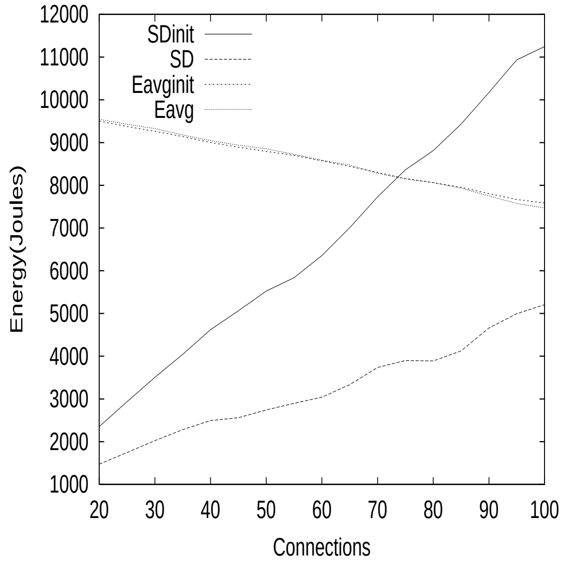


Fig. 6. Deviation and average energy on increasing connections for distributed algorithm

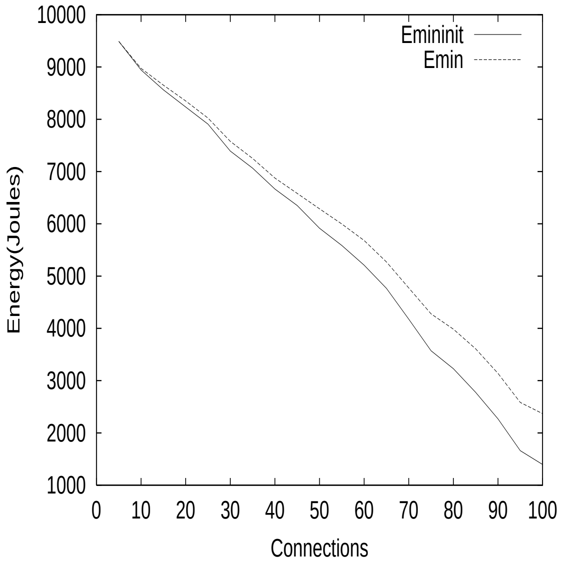


Fig. 5. Minimum Residual energy on increasing connections for online algorithm

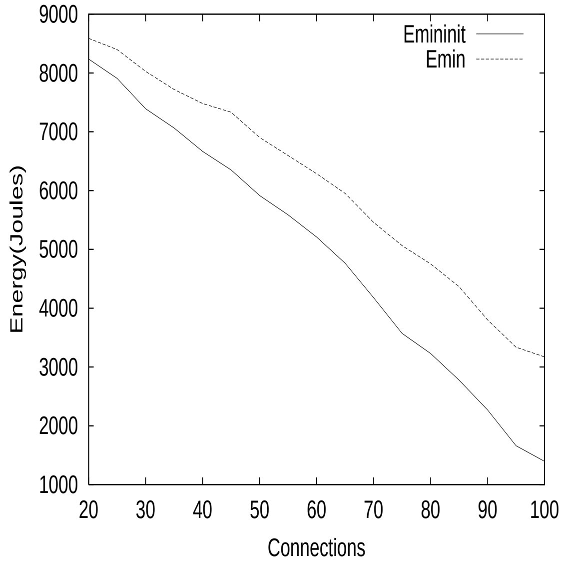


Fig. 7. Minimum Residual energy on increasing connections for distributed algorithm

Note that our static offline approach minimizes variance across all connections, even though there might be node-disjoint connections whose energy consumption (in their nodes) are unrelated to each other. However, from the birthday problem [22] it easy to see that, with a sufficient number of connections, the probability that two connections are node-disjoint is relatively low.

We point out that it is not always the case that direct transmission incurs higher energy consumption than network transmission [19]. For example, consider Figure 8, where source is node B and destination is node C for a connection of duration t. Let the length of edges AB and AC be a and let $\angle BAC$ be θ. Therefore BC has length $c = 2asin\frac{\theta}{2}$. Assume that the power required for distance d is d^2 and consider the case when $c > a$. Then in this case if we take the network route from B to C (via A), we will spend at least $2a^2t$ amount of energy whereas if we transmit directly from B to C we will spend $4a^2sin^2\frac{\theta}{2}t$ units of energy. Now for $0 < \theta < 90$ transmitting directly from B to C takes less energy than by going through A. This argument can be extended to paths involving more than two hops. So in a high-density topology there is a chance that the total energy spent in direct transmission across the nodes maybe less than the energy spent in taking a network-assigned route for many source-destination pairs.

Finally, note that the distributed heuristic resulted in significant benefits but somewhat less than the offline version. This is because the algorithm used only local information, disregarding the connection pattern across the whole network. The implica-

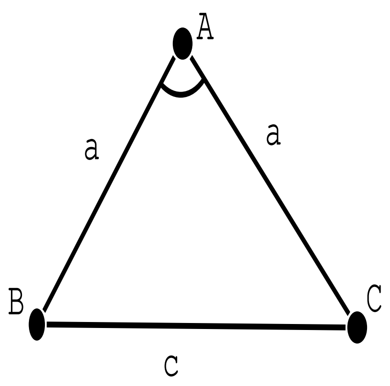


Fig. 8. Example1

tion is that some benefits can be realized from using only local information, but that the objective function is sufficiently complex that network-wide information must be used to achieve the variance reduction possibly through a centralized approach. In a distributed implementation, such information can be periodically broadcast in the same way that OSPF broadcasts link state information for shortest path computations. Note also that the online algorithm is not effective because the choices of the x_j are made sequentially, which means that early choices are based on little information and greatly affect the later choices. The implication again is that periodic exchange of information is likely to create the best results in practice.

IX. Conclusions

A high variance in nodal energy consumption can cause network disconnection starting with the first battery death. While some past efforts have considered routing mechanisms to address fairness (energy balance), we take a new and complementary approach in this paper: connections are segmented so that some segments use direct transmission instead of the network path. We formulated an optimization problem and presented an iterative algorithm. We found that variance reduction is significant at the expense of some reduction in average residual energy. Online and distributed algorithms were also presented.

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