Routing for Maximum System Lifetime in Wireless Ad-hoc Networks *

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Abstract

An ad-hoc network of wireless static nodes is considered as it arises in a rapidly deployed, sensor based, monitoring system. Information is generated in certain nodes and needs to reach some designated gateway node. Each node may adjust its power within a certain range that determines the set of possible one hop away neighbors. Traffic forwarding through multiple hops is employed when the intended destination is not within immediate reach. The nodes have limited initial amounts of energy that are consumed in different rates depending on the power level and the intended receiver. We propose algorithms to select the routes and the corresponding power levels such that the time until the batteries of the nodes drain-out is maximized. The algorithms are local and amenable to distributed implementation. When there is a single power level, the problem is reduced to a maximum flow problem with node capacities and the algorithm converges to the optimal solution. When there are multiple power levels then the achievable lifetime is within 90% of the optimal (that is computed by linear programming) most of the time. It turns out that in order to maximize the lifetime, the traffic should be routed such that the energy consumption is balanced among the nodes in proportion to their energy reserves, instead of routing to minimize the absolute consumed power.

1 Introduction

Consider a group of wireless static nodes randomly distributed in a region as in Figure 1, where each node has a limited battery energy supply used mainly for the transmission of data. Assume that at each node some type of information is generated, and the information needs to be delivered to some nodes designated as gateway nodes. These wireless nodes are assumed to have the capability of packet forwarding, i.e., relaying an incoming packet to one of its neighboring nodes, and the transmit power level can be adjusted to a level appropriate for the receiver to be able to receive the data correctly if the receiver is within the transmission range. Upon or before a new arrival of information either generated at the node itself or forwarded from the other nodes, routing decision has to be made so that the node knows which of its neighboring nodes to send its data to.

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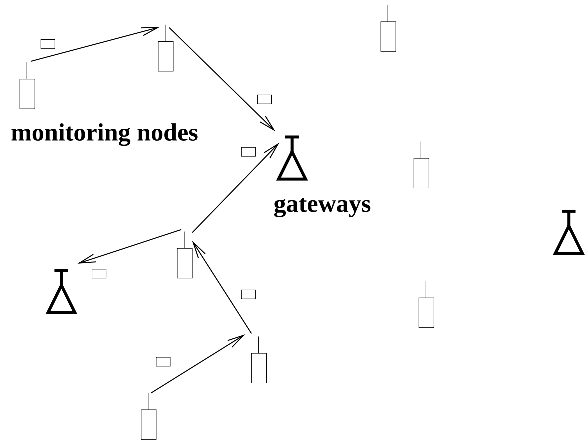


Figure 1: A multi-hop wireless ad-hoc network is depicted where the information generated at the monitoring nodes are delivered to the gateway nodes.

Note that the routing decision and the transmission energy level selection are intrinsically connected in this power-controlled ad-hoc network since the power level will be adjusted depending on the location of the next hop node.

An example scenario for this type of wireless ad-hoc network may include a wireless sensor network where the sensors gather acoustic, magnetic, or seismic information and send the information to its gateway node which has more processing power for further processing of the information or has larger transmission range for the delivery of the information to a possibly larger network for retrieval by a remote user.

Most of the previous works on routing in wireless ad-hoc networks deal with the problem of finding and maintaining correct routes to the destination during mobility and changing topology [1, 4, 9]. In [1, 4], the authors presented a simply implementable algorithm which guarantees strong connectivity and assumes limited node range. Shortest-path algorithm is used in this strongly connected backbone network. However, the route may not be the minimum energy solution due to possible omission of the optimal links at the time of the backbone connection network calculation. In [9], the authors developed a dynamic routing algorithm for establishing and maintaining connection-oriented sessions which uses the idea of predictive re-routing to cope with the unpredictable topology changes. Some other routing algorithms in mobile wireless networks can be found in [13, 10, 7, 12], which, as the majority of routing protocols in mobile ad-hoc networks do, use shortest-path routing where the number of hops is the path length.

The problem of minimum energy routing has been addressed before in [1, 4, 14, 8, 6, 16, 15], and [5]. The approach in those works was to minimize the consumed energy to reach the destination. If all the traffic is routed though through the minimum energy path to the destination the nodes in that path will be drain-out of batteries quickly while other nodes, which perhaps will be more power hungry if they forward traffic through them, will remain intact. Instead of trying to minimize the consumed energy, we address directly the performance objective of interest, that is to maximize the lifetime of the system. In order to achieve this, it turns out that it is more important to route the traffic such that the energy consumption is balanced among the nodes in proportion to their available energy instead of minimizing the absolute consumed power. In our study the topology of the network is static and the routing accounts to finding the traffic splits that balance optimally the energy consumption. Hence the results are applicable to networks which are either static, like the sensor networks we mentioned earlier, or their topology changes slowly enough such that there is enough time for optimally balancing the traffic in the periods between successive topology changes.

This paper is organized as follows: In section 2, the problem is formulated. In section 3, we propose a flow redirection algorithm. In section 4, we propose the maximum residual energy path routing algorithm. In section 5, random graphs are generated in order to evaluate the performances of these three algorithms.

2 Flows, Optimal Energy Consumption and Transmission Power Levels

Consider a directed graph $G(N, A)$ where N is the set of all nodes and A is the set of all directed links (i, j) where $i, j \in N$. Let S_i be the set of nodes that can be reached by node i with a certain power level in its dynamic range. We assume that link (i, j) exists if $j \in S_i$. Let each node i have the initial battery energy E_i, and let Q_i be the rate at which information is generated at node i. The transmission energy required for node i to transmit a bit to its neighboring node j is e_{ij}, and the rate at which information is transmitted from node i to node j is called the flow q_{ij}. We have a set of origin nodes O where the information is generated, and a set of destination nodes D among which any node can be reached in order for the information transfer be considered done.

The conservation of flow condition at each node i is assumed, i.e., the sum of all incoming flow must be the same as the sum of all outgoing flow,

$$\sum_{j:\ i \in S_j} q_{ji} + Q_i = \sum_{k \in S_i} q_{ik}, \quad \forall\ i \in N - D. \tag{1}$$

Subject to this constraint, we would like to maximize the lifetime of the network. The time it takes for the battery of node i to drain out under flow $\mathbf{q} = \{q_{ij}\}$ is given by

$$T_i(\mathbf{q}) = \frac{E_i}{\sum_{j \in S_i} e_{ij} q_{ij}}. \tag{2}$$

System lifetime : The lifetime of the system under flow q is defined as the minimum battery lifetime over all nodes,

$$T_{sys}(\mathbf{q}) = \min_{i \in N} T_i(\mathbf{q}). \tag{3}$$

Using the definition of the system lifetime, we can express the problem as follows:

$$\max_{\mathbf{q}}\ T_{sys}(\mathbf{q}), \quad \text{or equivalently,} \quad \max_{\mathbf{q}} \min_{i \in N} \frac{E_i}{\sum_{j \in S_i} e_{ij} q_{ij}}, \tag{4}$$

subject to (1), the flow conservation.

One can observe that the problem of maximizing the system lifetime given the information generation rates is equivalent to a linear programming problem[11] given by

$$\begin{aligned} & & \text{Maximize}\quad T & & & (5)\\ \text{s.t.} & & \hat{q}_{ij} \geq 0, & & \forall j \in S_i,\ \forall i \in N - D, & (6)\\ & & \textstyle\sum_{j \in S_i} e_{ij} \hat{q}_{ij} \leq E_i, & & \forall i \in N - D, & (7)\\ & & \textstyle\sum_{j:\ i \in S_j} \hat{q}_{ji} + T Q_i = \sum_{k \in S_i} \hat{q}_{ik}, & & \forall i \in N - D, & (8) \end{aligned}$$

where $\hat{q}_{ij} = T q_{ij}$ is the amount of information transfered during T from node i to j.

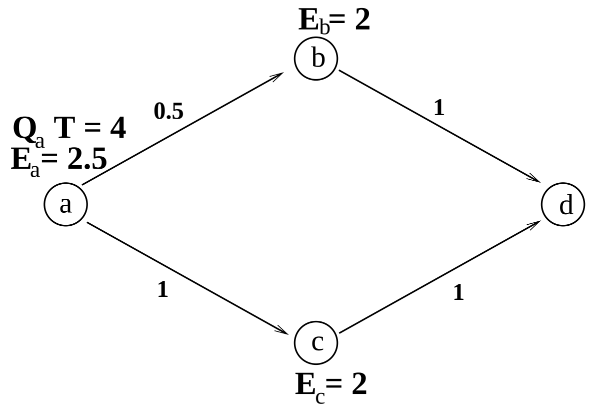


Figure 2: Counterexample to sufficiency of feasibility.

The formulation can be viewed as a variation of the conventional maximum flow problem with node capacities[3] in the special case where the transmitted power level at each node is fixed regardless of its next hop node, i.e., $e_{ij} = e_i$, for all $j \in S_i$, then (7) can be replaced by a set of node constraints

$$\sum_{j \in S_i} \hat{q}_{ij} \leq E_i/e_i, \ \forall i \in N - D. \tag{9}$$

In the following, we discuss conditions for the feasibility in order to attack the above problem from a different angle. For a set of nodes V, assume that each node $i \in V$ has the information generation rate Q_i which needs to be delivered out of V. For a node $i \in V$ let e_i^V be the least energy expenditure for transporting an information unit out of V. If there is no outgoing link of i through which information can be forwarded out of V, $e_i^V = \infty$ by convention. The necessary feasibility condition for the system lifetime to be longer than T is given by

$$\sum_{i \in V} TQ_i \leq \sum_{i \in V} \frac{E_i}{e_i^V}. \tag{10}$$

Note that $\frac{E_i}{e_i^V}$ is the maximum amount of information that can flow out of V via node i.

The following counterexample shows that the necessary condition is not sufficient. In Figure 2 one can verify that the necessary feasibility condition is met. However, the flow is not feasible since the total energy constraint at node a corresponding to (7),

$$0.5\hat{q}_{ab} + (4 - \hat{q}_{ab}) \leq 2.5, \tag{11}$$

requires $\hat{q}_{ab} \geq 3$, which together with the flow conservation condition at node b violates the total energy constraint at node b. It can be verified that if the energy expenditure through all the outgoing links of a sensor were the same then the necessary condition would be sufficient as well. In other words, if the transmit power levels are fixed, then the condition becomes both necessary and sufficient for feasibility.

3 Flow Redirection Algorithm

In this section, we propose a flow redirection algorithm (FR), which is motivated by the following observation.

Theorem 1 (Necessary optimality condition) *If the minimum lifetime over all nodes is maximized then the minimum lifetime of each path flow from the origin to the destination with positive flow has the same value as the other paths.*

Proof : Assume that the minimum lifetime over all nodes is maximized. If we further assume that the minimum lifetimes of the paths with positive flow to the destination are not all identical then there is a path with positive flow whose minimum lifetime is smaller than that of any other path flows. We can always increase the minimum lifetime of this path, which is also the minimum lifetime over all nodes, by shifting arbitrarily small amount of flow $\epsilon > 0$ from the former path to one of the latter paths such that the minimum lifetime of the latter path after the shift is still larger than the minimum lifetime over all nodes before the shift. This contradicts our assumption that the minimum lifetime over all nodes is maximized. □

3.1 Algorithm Description

The algorithm FR tries to balance the minimum lifetime of each flow path by using an iterative feasible descent method. The main idea of FR is to redirect a portion of the current flow at each node i in a way that the minimum lifetime over all nodes will increase so that the resulting flow to the destination will eventually have the same lifetime in all paths, which satisfies the necessary optimality condition stated in Theorem 1.

In the following, we describe the implementation of FR. Let's use an imaginary super source node s where $S_s = O$, and an imaginary super sink node $\tilde{d}$ where $\tilde{d} \in S_d$ for all $d \in D$. Let $e_{so} = 0$ for all $o \in O$ and $e_{d\tilde{d}} = 0$ for all $d \in D$, and let E_s and E_d be any positive constant. Let the initial flow be such that $q_{so} = Q_o$ and from o to $\tilde{d}$ the minimum transmitted energy path is used with a flow value Q_o for each $o \in O$. Note, however, that any feasible flow may be used as the initial flow. Each node $i \in N - D$ redirects its outgoing flow by subtracting ϵ_i from the flow of a certain path to the destination and by adding the same amount to the flow of another path to the destination. The steps to be taken at each node $i \in N - D$ are: i) Determine the from which path to which path; ii) Calculate ϵ_i, the amount of redirection; iii) Redirect the flow properly

Let P_i be the set of all paths from node i to the destination node $\tilde{d}$. For a path $p \in P_i$, define the path length $L_p(\mathbf{q})$ as a vector whose elements are the lifetimes of all the nodes in the path. For example, if path $p \in P_i$ starting from node i traverses nodes $j_1, j_2, \cdots, j_m$ where $j_m \in D$, then $L_p(\mathbf{q}) = [T_i(\mathbf{q}), T_{j_1}(\mathbf{q}), T_{j_2}(\mathbf{q}), \cdots, T_{j_{m-1}}(\mathbf{q})]$. The length of path p, $L_p(\mathbf{q})$ is said to be longer than the length of path p', $L_{p'}(\mathbf{q})$ if the smallest element of $L_p(\mathbf{q})$ is larger than that of $L_{p'}(\mathbf{q})$. In case they are the same, the next smallest elements are compared, and so on. Using this so-called lexicographical ordering, the longest length path between any two nodes can be defined. We modify the distance comparison part of the Bellman-Ford algorithm [2] to obtain the longest length paths distributively. Let's denote the longest length path from node i to the destination node $\tilde{d}$ as $l(i)$.

The first step of the algorithm at each node i is described in more detail. Let's denote the next hop nodes by g and t where we would like to redirect the flow q_{ig} to the flow q_{it}, where $g \in S_i$ and $t \in S_i$ are to be carefully chosen among the neighboring nodes of node i.

First of all, among the downstream neighboring nodes of node i, find the node whose longest path length to the destination is the smallest, and call it h, i.e.,

$$h = \underset{j \,:\, j \in S_i,\ q_{ij} > 0}{\text{argMIN}} \; L_{l(j)}(\mathbf{q}), \tag{12}$$

where MIN denotes the minimum in the lexicographical ordering.

Now, depending on whether the lifetime of node i, $T_i(\mathbf{q})$ is larger than the minimum lifetime of this path, two different measures are taken.

If $T_i(\mathbf{q}) \leq \min[L_{l(h)}(\mathbf{q})]$ then we would like to increase the lifetime of node i. This can be achieved if we redirect the flow at node i from the direction where the required transmission energy per bit is the largest to the direction whose longest path length to the destination is the largest among all neighboring nodes of i with smaller transmission energy per information unit. That is,

$$g = \underset{j\,:\,j \in S_i,\ q_{ij}>0}{\text{argmax}}\ e_{ij}, \tag{13}$$

and

$$t = \underset{j\,:\,j \in S_i,\ e_{ij}<e_{ig}}{\text{argMAX}}\ L_{l(j)}(\mathbf{q}), \tag{14}$$

where MAX is the maximum in the lexicographical ordering. Note that $l(t)$ doesn't have to be the largest longest path, it suffices to have less energy consumption per bit transmission. In our algorithm, we alternately choose t to be the one with the minimum energy consumption per bit transmission, i.e.,

$$t = \underset{j\,:\,j \in S_i}{\text{argmin}}\ e_{ij}. \tag{15}$$

On the other hand, if $T_i(\mathbf{q}) > \min[L_{l(h)}(\mathbf{q})]$ then we would like to increase the length of the smallest longest length path. This can be achieved if we redirect the flow from the smallest longest length path to the largest longest length path. That is,

$$g = h, \tag{16}$$

and

$$t = \underset{j \in S_i}{\text{argMAX}}\ L_{l(j)}(\mathbf{q}). \tag{17}$$

Note that $l(t)$ doesn't have to be the largest longest path, it suffices to have larger minimum lifetime than that of the smallest longest path $l(h)$. In our algorithm, we alternately choose t to be the one with the minimum energy consumption per bit transmission.

$$t = \underset{j\,:\,j \in S_i, min[L_{l(j)}(\mathbf{q})]>min[L_{l(h)}(\mathbf{q})]}{\text{argmin}}\ e_{ij}. \tag{18}$$

The second step of the algorithm at each node i is described in more detail. The constraints that ϵ_i should meet are as follows. First, it should be less than or equal to q_{ig} since no one can give what doesn't exist, i.e.,

$$\epsilon_i \leq q_{ig}. \tag{19}$$

Furthermore, none of the lifetimes should become smaller than the currently minimum lifetime of the subnetwork consisting of node i and all downstream nodes since this will lead us to the opposite direction to that of our objective. By this, we guarantee the monotonic convergence of the algorithm. If $T_i(\mathbf{q}) \leq \min[L_{l(h)}(\mathbf{q})]$ then none of the lifetimes in the path $l(t)$ should become smaller than $T_i(\mathbf{q})$, i.e.,

$$\frac{1}{T_j(\mathbf{q})} + \frac{e_{jk}\epsilon_i}{E_j} \leq \frac{1}{T_i(\mathbf{q})}, \tag{20}$$

for any link (j,k) in the path $l(t)$. On the other hand if $T_i(\mathbf{q}) > \min[L_{l(h)}(\mathbf{q})]$ then we need to consider two things. First, none of the lifetimes in the path $l(t)$ should become smaller than the minimum lifetime of the path $l(g)$, i.e.,

$$\frac{1}{T_j(\mathbf{q})} + \frac{e_{jk}\epsilon_i}{E_j} \leq \frac{1}{\min[L_{l(g)}(\mathbf{q})]}, \tag{21}$$

for any link (j, k) in the path $l(t)$. Second, if $e_{it} > e_{ig}$ then the lifetime of node i may decrease due to the redirection, but it should not become smaller than the minimum lifetime of the path $l(g)$, i.e.,

$$\frac{1}{T_i(\mathbf{q})} + \frac{(e_{it} - e_{ig})\epsilon_i}{E_i} \leq \frac{1}{\min[L_{l(g)}(\mathbf{q})]}. \tag{22}$$

Finally, the value of ϵ_i should be chosen among the values that meet all the constraints stated above. We could either use the maximum ϵ_i that meets all the constraints or just a fraction of it. To avoid possible oscillations and for faster convergence, we choose the half of the maximum ϵ_i that meets all the constraints except for (19).

The third step of the algorithm at each node i is described in more detail. Adding ϵ_i to the path $l(t)$ is easy. We can simply add it to each link flows in the path. However, subtracting ϵ_i from the path $l(g)$ is not so easy since there may be some links in the path whose flow is less than ϵ_i. We start to subtract ϵ_i from q_{ig}, which is safe because of (19). Suppose that ϵ_i is larger than the flow q_{jk} at some link (j, k) in the path $l(g)$ where we want to subtract ϵ_i from. We use a recursive algorithm in this case. First, we subtract q_{jk} from q_{jk} and then continue subtracting this amount along the path $l(k)$, the longest length path from k to d. Second, we subtract the remaining $\epsilon_i - q_{jk}$ from the smallest longest path that starts from a downstream neighbor h' of node j, i.e.,

$$h' = \underset{x \,:\, x \in S_j,\ q_{jx} > 0}{\text{argMIN}} \; L_{l(x)}(\mathbf{q}). \tag{23}$$

If $\epsilon_i - q_{jk}$ is still larger than the flow $q_{jh'}$ then we successively try the next smallest longest path that starts from a downstream neighbor of node j, and so on.

Algorithm FR doesn't always converge to the global optimum. An example showing the convergence to the local optimum is presented in the following. While Figure 3 (a) is the global optimum, the algorithm may converge to Figure 3 (b) depending on the initial flow. The numbers correspond to the case when $\delta = 0.01$ in the figure, and again the information generation rate at the origin is assumed to be $Q_o = 1$. While the global optimal system lifetime is $T_{sys}^{opt} \approx 1.99$, the local optimum by FR is $T_{sys}^{FR} \approx 1.01$. In this case the ratio between the two is given by $R = 0.5075$, where the ratio

$$R = \frac{T_{sys}^{X}}{T_{sys}^{opt}} \tag{24}$$

will be used as the performance measure of algorithm X.

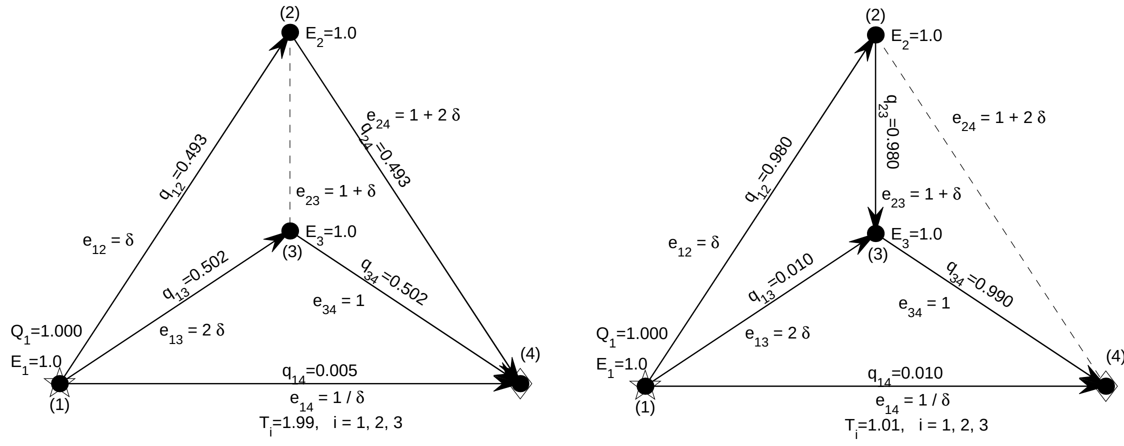
We could observe that as δ approaches zero the ratio between the local optimum and the global optimum approaches 0.5. We are not sure if this is indeed the worst case of FR as of yet. However, we haven't found any simulation result with $R < 0.5$.

4 Maximum Residual Energy Path Routing

In this section, we propose another algorithm based on Theorem 1 called the maximum residual energy path (MREP) routing algorithm.

Let P_i be the set of all paths from node i to the destination node $\tilde{d}$. For a path $p \in P_i$, define the path length L_p as a vector whose elements are the reciprocal of the residual energy for each link in the path after the route has been used by a unit flow. We assume that the routing path is calculated for each unit flow. The element of L_p for link (j, k) is

$$\frac{1}{\underline{\mathrm{E}}_j - e_{jk}\hat{u}}, \tag{25}$$



(a) (b)

Figure 3: An example showing local optimum convergence : (a) global optimum with $T_{sys}^{opt} \approx 1.9901$, (b) local optimum with $T_{sys}^{FR} \approx 1.0099$ when $\delta = 0.01$.

where $\underline{\mathrm{E}}_j$ is the residual energy at node j and $\hat{u}$ is a unit flow. By using the lexicographical ordering in this case by comparing the largest elements first and so on, shortest path from each node i to the destination can be obtained using a slightly modified version of the distributed Bellman-Ford algorithm. A unit flow is transmitted via the shortest path.

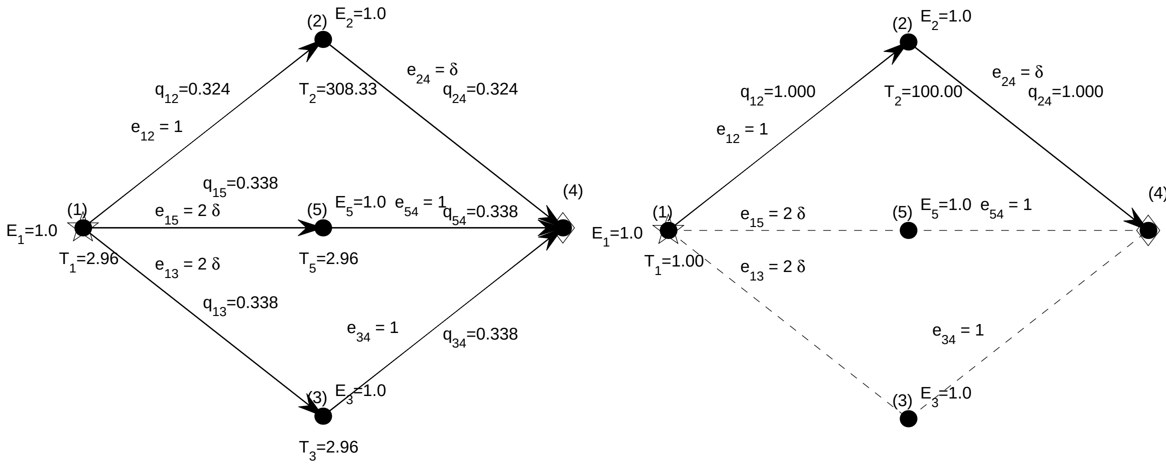
5 Performance Comparison through Simulation

In this section, random graphs are generated to evaluate the performances of the algorithms. The algorithms are compared with the conventional minimum transmitted energy (MTE) algorithm in order to see how much we gain in terms of the system lifetime by adopting the new problem formulation. MTE algorithm is a shortest path algorithm where the path length is the sum of energy expenditures per bit transmission over each link in the path.

We can find a pathologic example where the ratio between the maximum lifetime of the system obtained by MTE and the true optimum is close to zero. Consider Figure 4 for example where node 1 is the origin and node 4 is the destination. Assume that the information generation rate at the origin is $Q_o = 1$. While Figure 4 (a) shows the true optimum where $T_{sys}^{opt} \approx 2.96$, Figure 4 (b) shows that the maximum lifetime of the system obtained by MTE is $T_{sys}^{MTE} = 1.00$ when $\delta = 0.01$. This corresponds to $R \approx 0.3378$. As δ goes to zero the ratio R approaches $1/3$. By adding more nodes with the distance of 2δ from node 1 and with the distance of 1 to node 4 like node 5, the ratio R becomes approximately inversely proportional to the number of such nodes added.

Random graphs are generated according to the following description. Let there be 20 nodes randomly distributed in a square of size 5 by 5 among which 5 origin nodes and 2 destination nodes are randomly chosen. Let each node i have initial energy $E_i = 1$ and the information generation rate at each origin node $o \in O$ is $Q_o = 1$. We assume that the transmission range of each node is limited by 2.5. The energy expenditure per bit transmission from node i to j is given by

$$e_{ij} = \left\{ \max\left(0.01, \frac{d_{ij}}{2.5}\right) \right\}^4 , \tag{26}$$



(a) (b)

Figure 4: An example showing MTE's arbitrarily poor performance : (a) true optimum with $T_{sysx}^{opt} \approx 2.96$, (b) system lifetime obtained by MTE, $T_{sys}^{MTE} = 1.00$ when $\delta = 0.01$.

where $d_{ij} \leq 2.5$ is the distance between nodes i and j. Note that there may be cases where no path is available between the origin and the destination. We simply discard those cases to assume the connectivity.

The performances of the MTE, FR, and MREP are compared in Table 1.

Table 1: The performance comparison of the three algorithms.

R	MTE	FR	MREP
average	0.7519	0.9538	0.9607
worst case	0.2160	0.6567	0.8349
over 0.9	37 %	84 %	89 %

On the average, FR and MREP were both close to optimum with comparable performances, while MTE was not as good as the two. While the mean of the ratio R of MTE was about 0.75, that of FR and MREP were about 0.96. The ratio R of FR and MREP were over 90 % of the true optimum in 84 % and 89 % of the case respectively, while that of MTE was so in only 37 % of the case. The worst case performance of MTE was 0.2160 of the optimum. Note that the performance of MTE was shown to be arbitrarily bad. The worst case of FR was 0.6567, and the worst case of MREP was 0.8349 which is better than that of FR.

6 Conclusion

A routing problem in a power-controlled wireless ad-hoc network of static nodes was formulated. We assumed that the limited battery energy is the single most important resource and hence formulated the problem as to maximize the battery lifetime of the system for a set of given information generation rates at the origin nodes. In order to maximize the lifetime, the traffic is routed such that the energy consumption is balanced among the nodes in proportion to their energy reserves, instead of routing to minimize the absolute consumed power. We proposed the flow redirection algorithm and the maximum residual energy path routing algorithm that are local and amenable to distributed implementation with close to optimal performance most of the time.

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