Maximum Lifetime Routing in Wireless Sensor Networks

Jae-Hwan Chang and Leandros Tassiulas

***Abstract*— A routing problem in static wireless ad-hoc networks is considered as it arises in a rapidly deployed, sensor based, monitoring system known as the wireless sensor network. Information obtained by the monitoring nodes needs to be routed to a set of designated gateway nodes. In these networks, every node is capable of sensing, data processing, and communication, and operates on its limited amount of battery energy consumed mostly in transmission and reception at its radio transceiver. If we assume that the transmitter power level can be adjusted to use the minimum energy required to reach the intended next hop receiver then the energy consumption rate per unit information transmission depends on the choice of the next hop node, i.e., the routing decision. We formulate the routing problem as a linear programming problem, where the objective is to maximize the network lifetime, which is equivalent to the time until the network partition due to battery outage. Two different models are considered for the information generation processes. One assumes constant rates and the other assumes an arbitrary process. A shortest cost path routing algorithm is proposed which uses link costs that reflect both the communication energy consumption rates and the residual energy levels at the two end nodes. The algorithm is amenable to distributed implementation. Simulation results with both information generation process models show that the proposed algorithm can achieve network lifetime that is very close to the optimal network lifetime obtained by solving the linear programming problem.**

***Keywords*— energy-sensitive routing, power aware routing, wireless sensor networks, wireless ad-hoc networks**

1 Introduction

Consider a wireless network of static nodes randomly distributed as depicted in Figure 1, where each node operates on limited battery energy consumed mostly in transmission and reception of data at its radio transceiver. Assume that at each node some type of information is generated and the information needs to be delivered to a set of designated gateway nodes possibly using multiple hops. The transmitter power level is assumed to be adjusted to the minimum level appropriate for the intended receiver within the transmission range. Note that the routing decision and the transmission energy level selection are intrinsically connected in these power-controlled wireless ad-hoc networks since the power level will be adjusted depending on the choice of the next hop node.

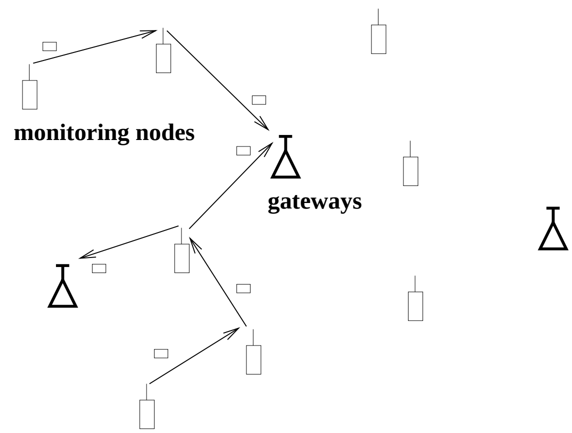


Figure 1: A wireless sensor network is depicted where the nodes are randomly distributed and the information generated at the monitoring nodes are to be delivered to the gateway nodes.

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, 7, 22]. In [1, 7], 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. In [22], 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 [26, 23, 14, 25], which, as the majority of routing protocols in mobile ad-hoc networks do, use shortest path or minimum hop (MH) routing.

Power consumption in the wireless ad-hoc networks can be largely categorized into two parts. One is communica-

This paper was partially presented at the 37-th Annual Allerton Conference on Communication, Control, and Computing, Monticello, IL in 1999, the IEEE INFOCOM 2000, Tel Aviv, Israel in 2000, and the Advanced Telecommunications and Information Distribution Research Program (ATIRP'2000), College Park, MD in 2000.

This work was partly supported by an ONR Young Investigator Award N000149710735 and AFOSR grant F496200110197.

J.-H. Chang is with Telecommunication R&D Center of Samsung Electronics Co., Ltd., Suwon, Korea. E-mail: jchang@ieee.org.

L. Tassiulas is with the Institute for Systems Research and the Department of Electrical and Computer Engineering, University of Maryland, College Park, MD 20742, USA. E-mail: leandros@isr.umd.edu.

tion related and the other is non-communication related such as processing or sensing (in case of a sensor network). A model for evaluating the communication related energy consumption behavior of a mobile ad-hoc network was presented in [9], where the power consumption was further categorized into three modes: transmission, reception, and idle mode. Power saving in idle mode was studied in [36], which we believe is complementary to our work. However, we, as well as the others mentioned in the following, have been focusing in power savings during transmission and reception. In [11], the sum of multiples of the transmission power and the power price was proposed as the path length to be minimized. The power price was a function of the current battery level, total storage capacity, type of battery, etc., but they didn't specify the metric. In [32], the conditional max-min battery capacity routing (CMMBCR) was proposed, which is a combination of minimum total energy (MTE) routing and max-min residual energy routing. The minimum total transmission and reception energy path is chosen in the set of all paths whose minimum residual energy is above a given threshold. If the set if empty then max-min residual energy route is used. In [18], routing for the maximum network lifetime was studied, where the message sequence is not known a priori. An approximation algorithm called *max-min* zP_{min} was proposed which tries to strike a balance between the minimum transmission energy routing and the max-min residual energy routing. Scalability of the algorithm was provided by zone-based hierarchical routing approach. Reception energy consumption is assumed to be included in the transmission energy consumption since all intermediate nodes except the source and the destination are engaged in both transmission and reception. The performance of their algorithm was shown to be close to the optimal solution obtained by linear programming. The *max-min* zP_{min} algorithm first finds the minimum transmission energy path (let the total transmission energy on this path be P_{min}) and then removes all edges whose residual energy fraction after use is smaller than or equal to the minimum residual energy fraction on the minimum transmission energy path. It then repeats the same procedure on the subgraph until just before the total transmission energy of the chosen path exceeds z times P_{min}, where $z \geq 1$. The resulting path is assigned to the incoming traffic. In [31], a routing metric similar to ours have been used. However, instead of requiring the global network information they only require localized routing information and assume that non-local routing information can be treated equally in all paths. Refer to [20] for a good survey on the power optimization in routing protocols.

The problem of minimum energy routing has been addressed before in [1, 7, 28, 21, 10, 30, 29], and [8]. The approach in these papers, called the minimum total energy (MTE) routing here, was to minimize the total consumed energy to reach the destination, which minimizes the energy consumed per unit flow or packet. However, if all the traffic is routed through the minimum energy path to the destination, the nodes in that path will run out of batteries quickly rendering other nodes useless due to a network partition even if they do have available energy resource. In our work, instead of trying to minimize the total consumed energy on the path, the performance objective of maximizing the lifetime of the system[4], which is equivalent to maximizing the time to network partition[30] has been considered. In [4] we identified the maximum lifetime problem as a linear programming problem and in [5] the problem was extended to the multicommodity case. Since it is a linear programming problem, it is solvable in polynomial time. While in [5] constant information generation rate case was considered, in [6] some arbitrary information generation process model was studied.

In this paper, the maximum lifetime routing problem is extended to include the energy consumption at the receivers during reception. Note, however, that the energy consumption at the unintended receiver nodes that overhear the transmission is not included. This extension was applied to the algorithm as well. In the simulation, comparison is made with the optimal network lifetime obtained by solving the linear programming problem as well as with two other algorithms proposed in [32] and [18]. Note that due to the inherent non-scalability of table-driven routing approach, the proposed solution in its current form is not scalable and hence may not be suitable for direct application to large networks. Note also that the energy consumption due to routing control packets are not included in the model or the simulation since we assume a situation where the energy consumption is dominated by the data packets. However, in the simulation we show that there is a tradeoff between the routing information update rate and the performance so that the number of routing control packets can be reduced with some sacrifice in the performance.

Brown et al.[3] have extended the objective of power-aware routing in the multicommodity case to sequentially maximizing the lifetime of each commodity, while we only maximize the time until the first commodity network partition.

Information from other sources were utilized for the routing decision in the following works. Geographical information of the communication nodes is used in [16, 15, 31, 34], and [36]. Upper layer information is utilized in [13, 17], and [12].

Distributed topology control was studied in [27] and [33] where transmitter power levels are selected to guarantee the network connectivity while saving transmission energy, which can be complementary to our work. A good survey on the topology control, clustering, broadcasting, and multicasting can be found in [19].

In our study the nodes are not mobile and the topology of the network is static. Hence the results are applicable to networks which are either static, like the sensor networks we mentioned earlier, or whose 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 maximum system lifetime routing problem is formulated for fixed information generation rates as well as for some arbitrary information generation process. In Section 3, we propose the flow augmentation (FA) algorithm which iteratively augments traffic flow along the shortest cost path. The proposed link cost reflects both the residual energy at the transmitting node and the receiving node and the energy consumption in unit data transmission over the link. In Section 4, simulation on randomly generated graphs is performed to evaluate the performance of the proposed algorithm both for the fixed information generation rates and for a certain scenario where information is generated at monitoring nodes that detect moving targets. Finally in Section 5, some concluding remarks are made.

2 Routing for the Maximum System Lifetime

In this section, we first formulate the maximum system lifetime routing problem for the case where information generation rates are fixed. And then, we consider a more general case where we are given some arbitrary information generation processes instead of fixed information generation rates.

2.1 Constant Information Generation Rates

A wireless sensor network is modeled as 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 $i, j \in N$. Link (i, j) exists if and only if $j \in S_i$, where S_i is the set of all nodes that can be directly reached by node i with a certain transmit power level in its dynamic range. Each node i has the initial battery energy of E_i. The transmission energy consumed at node i to transmit a data unit to its neighboring node j is denoted by e^t_{ij} and the energy consumed by the receiver j is denoted by e^r_{ij}. Let there be multiple commodities where a commodity is defined by a set of source nodes and destination nodes. We are given, for each commodity $c \in C$, a set of origin nodes $O^{(c)}$ where information is generated at node i with rate $Q^{(c)}_i$, i.e.,

$$O^{(c)} = \{\ i \mid Q^{(c)}_i > 0,\ i \in N\}, \qquad (1)$$

and a set of destination nodes $D^{(c)}$ among which any node can be reached in order for the information transfer of commodity c to be considered done. Let $q^{(c)}_{ij}$ be the transmission rate of commodity c from node i to node j to be assigned by the routing algorithm.

The lifetime of node i under a given flow $\mathbf{q} = \{q^{(c)}_{ij}\}$ is given by

$$T_i(\mathbf{q}) = \frac{E_i}{\sum_{j \in S_i} e^t_{ij} \sum_{c \in C} q^{(c)}_{ij} + \sum_{j: i \in S_j} e^r_{ji} \sum_{c \in C} q^{(c)}_{ji}}. \qquad (2)$$

Now, let us define the *system lifetime* or the *network lifetime* under flow $\mathbf{q}$ as the minimum lifetime over all nodes, i.e.,

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

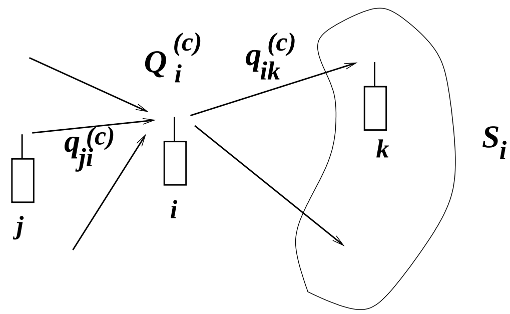


Figure 2: Conservation of flow condition at node i for each commodity c requires that the sum of information generation rate and the total incoming flow must equal the total outgoing flow.

Note that in our flow model with fixed information generation rates the system lifetime is equivalent to the earliest network partition time of a commodity and is by definition the time of the first node death.

Our goal is to find the flow that maximizes the system lifetime under the flow conservation condition. Note that maximizing the system lifetime is equivalent to maximizing the amount of total information transfer given a fixed information generation rates. The problem can be written as follows:

$$\begin{aligned}
&\text{Maximize} \quad T_{sys}(\mathbf{q}) \\
&\text{s.t.} \quad q^{(c)}_{ij} \geq 0, \qquad \forall i \in N, \forall j \in S_i, \forall c \in C, \\
&\sum_{j:\ i \in S_j} q^{(c)}_{ji} + Q^{(c)}_i = \sum_{j \in S_i} q^{(c)}_{ij}, \quad \forall i \in N - D^{(c)}, \forall c \in C.
\end{aligned} \qquad (4)$$

Figure 2 illustrates the flow conservation condition for commodity c at node i, and it should be noted that the condition applies to each commodity separately.

In the following we show that the problem is a linear programming problem[24]. The problem of maximizing the system lifetime, given the information generation rates $Q^{(c)}_i$ at the set of origin nodes $O^{(c)}$ and the set of destination nodes $D^{(c)}$ for each commodity c, is equivalent to the following linear programming problem:

$$\begin{aligned}
&\text{Maximize} \quad T \\
&\text{s.t.} \quad \hat{q}^{(c)}_{ij} \geq 0, \qquad \forall i \in N,\ \forall j \in S_i,\ \forall c \in C, \\
&\sum_{j \in S_i} e^t_{ij} \sum_{c \in C} \hat{q}^{(c)}_{ij} + \sum_{j:\ i \in S_j} e^r_{ji} \sum_{c \in C} \hat{q}^{(c)}_{ji} \leq E_i, \quad \forall i \in N, \\
&\sum_{j:\ i \in S_j} \hat{q}^{(c)}_{ji} + T Q^{(c)}_i = \sum_{j \in S_i} \hat{q}^{(c)}_{ij}, \quad \forall i \in N - D^{(c)}, \forall c \in C,
\end{aligned} \qquad (5)$$

where $\hat{q}^{(c)}_{ij} = T q^{(c)}_{ij}$ is the amount of information of commodity c transmitted from node i to node j until time T. Note that the variable T in (5) should be considered as an independent variable in order to see the equation as a linear programming problem.

2.2 Arbitrary Information Generation Processes

In this section, a more practical scenario than the one introduced in the previous section will be considered for wireless sensor networks. Instead of having a fixed set of origin nodes with fixed information generation rates, a packet is generated periodically[1] at each sensor node if the sensor is detecting a moving target. For simplicity, we assume that there is only one commodity in this case, which means that all information has the same set of destination nodes.

Notice the difference between the problem discussed here with the previous one. In the previous problem, we were given fixed information generation rates, which implied that the amount of information generated in some time interval T is known a priori. On the contrary, here we assume that the amount of total information generated in some time interval T is not known a priori but we try to make routing decision on the fly as new information is generated. In this scenario, a number of sensors are randomly distributed, and target objects move about in or pass through the region. Each sensor generates a packet periodically if and only if there is any target object in its sensor range. The generated packets are to be delivered to one of the designated gateway nodes. Our goal is to select the route of each generated packet such that the time until the first failure of the packet delivery due to battery outage is maximized.

In the following paragraph, we will describe an integer programming problem the solution of which will be used as a performance bound for the problem that we are trying to solve. As mentioned earlier, the problem we are interested in assumes no knowledge about the future information generation processes. However, for the following performance bound we will assume the perfect knowledge of the future information generation processes.

Let's consider the feasibility problem first. We would like to determine if the information generated until time T can be delivered to one of the set of destination nodes D. Let $\hat{Q}_i(T)$ be the number of packets generated at origin node $i \in O$ during the time interval $[0, T)$, and let $\hat{q}_{ij}(T)$ be the total number of packets routed through link $(i, j) \in A$. It is feasible if there exists a set of non-negative integers $\hat{q}_{ij}(T)$ for each link $(i, j) \in A$ which satisfies the following two conditions. The conservation of flow condition is given by

$$\sum_{j:\ i \in S_j} \hat{q}_{ji}(T) + \hat{Q}_i(T) = \sum_{j \in S_i} \hat{q}_{ij}(T),\ \forall i \in N - D, \qquad (6)$$

and the total energy constraint is given by

$$\sum_{j \in S_i} e^t_{ij} \hat{q}_{ij}(T) + \sum_{j:\ i \in S_j} e^r_{ji} \hat{q}_{ji}(T) \le E_i,\ \forall i \in N, \qquad (7)$$

[1] Although it doesn't have to be periodic, it is assumed so for simplicity. In case it's not periodic, the lifetime will not be readily given in absolute time units such as in seconds but in number of possibly unequal discrete time units.

where e^t_{ij} and e^r_{ij} are the energy consumption in transmitting and receiving one packet over the link (i, j) at nodes i and j respectively. Our goal in terms of this feasibility problem can be stated as finding the maximum feasible time T.

Note that the problem with constant information generation rates in the previous section is a special case of this more general formulation.

In the following, we discuss conditions for the feasibility. For a set of nodes V, assume that each node $i \in V$ has the amount of information generated during $[0, T)$, $\hat{Q}_i(T)$, which needs to be delivered out of V. For a node $i \in V$ let e^V_i 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, $e^V_i = \infty$. Assume here that no energy is consumed in reception for the simplicity of the discussion. The necessary feasibility condition is given by

$$\sum_{i \in V} \hat{Q}_i(T) \le \sum_{i \in V} \frac{E_i}{e^V_i}, \qquad (8)$$

which states that the total information generated should not be greater than the capacity of all outgoing flow paths. Note that $\frac{E_i}{e^V_i}$ is the maximum amount of information that can flow out of V via node i.

The following counterexample in Figure 3 shows that the necessary condition above is not sufficient. 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),

$$0.5\hat{q}_{ab}(T) + (4 - \hat{q}_{ab}(T)) \le 2.5, \qquad (9)$$

requires $\hat{q}_{ab}(T) \ge 3$, and the total energy constraint at node b requires $\hat{q}_{bd}(T) \le 2$, but at the same time $\hat{q}_{ab}(T) = \hat{q}_{bd}(T)$ should hold according to the flow conservation condition, which is impossible.

It can be verified that if the energy expenditure through all the outgoing links of a node 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 Augmentation Algorithm

In this section, we propose a heuristic called the flow augmentation (FA) algorithm which is an extension to what has bene presented in [5]. We will describe the algorithm for fixed information generation rates.

A high level description of the algorithm is given in the following for fixed information generation rates. At each iteration, each origin node $o \in O^{(c)}$ of commodity c calculates the shortest cost path to its destination nodes in $D^{(c)}$, where the cost will be defined later. Then the flow is augmented by an amount of $\lambda Q^{(c)}_i$ on the shortest cost path, where λ is the augmentation step size which is equivalent to the amount of information routed between routing

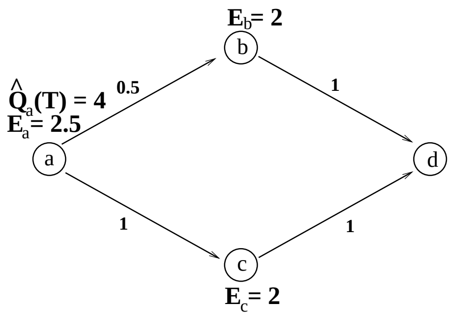


Figure 3: Counterexample showing that the necessary feasibility condition is not sufficient. The numbers next to the links are the energy expenditure per data unit transmitted across the link.

information updates. For example, if the routing information is updated after every packet is routed then this value represents the packet size. Residual energy at each node is updated just before each routing information update, which will change link costs. With the updated link costs, the shortest cost paths are recalculated and the procedures are repeated until any node $i \in N$ runs out of its initial total energy E_i.

Our objective is to find the best link cost function which will lead to the maximization of the system lifetime. There are some parameters to consider in calculating the link cost $cost_{ij}$ for link (i,j). They are the energy expenditure for unit data transmission over the link, e^t_{ij} and e^r_{ij}, the initial energy E_i and E_j, and the residual energy, $\underline{E}_i$ and $\underline{E}_j$. A good candidate for the flow augmenting path should consume less energy and should avoid nodes with small residual energy since we would like to maximize the minimum lifetime over all nodes. In [30], each of these parameters were separately considered, but the combinations of them were not. We propose a new link metric which combines these parameters in one. In the beginning when all the nodes have plenty of energy, the minimum total consumed energy path is desired, while as residual energy decreases it is more important to avoid the nodes with small residual energy. Therefore, the link cost function should be such that when the nodes have plenty of residual energy, the energy expenditure term is emphasized, while as the residual energy of a node becomes smaller the residual energy term should be given more weight.

With the above throughts in mind, the link cost $cost_{ij}$ is proposed to be

$$cost_{ij} = \left(e^t_{ij}\right)^{x_1} \underline{E}_i^{-x_2} E_i^{x_3} + \left(e^r_{ij}\right)^{x_1} \underline{E}_j^{-x_2} E_j^{x_3}, \qquad (10)$$

where x_1, x_2, and x_3 are nonnegative weighting factors for each item. The value of x_1 is chosen to be either one or zero. Note that if $x_1 = x_2 = x_3 = 0$ then the shortest cost path is the minimum hop path, and if $x_1 = 1$ and $x_2 = x_3 = 0$ then the shortest cost path is the minimum total energy path. If $x_2 = x_3 \neq 0$ then it means the normalized residual energy is used, while if $x_3 = 0$ then it means the absolute residual energy is used. Let's refer to the algorithm as FA(x_1, x_2, x_3) in the rest of the paper indicating the parameters. The meanings of the parameters are summarized in Table 1 for reference.

Table 1: Meanings of the parameters in the algorithm FA.

FA(x_1, x_2, x_3)	Meaning
FA$(0,0,0)$	`Minimum hop (MH) routing`
FA$(1,0,0)$	`Minimum total energy (MTE) routing`
FA$(\cdot, x, x)$	`Normalized residual energy is used`
FA$(\cdot, \cdot, 0)$	`Absolute residual energy is used`

The path cost is computed by the summation of the link costs on the path, and the algorithm can be implemented with any existing shortest path algorithms including the distributed Bellman-Ford algorithm[2].

Algorithm FA(x_1, x_2, x_3)

1. Calculate the shortest cost path for each commodity c with cost of link (i,j) given by
$$cost_{ij} = \left(e^t_{ij}\right)^{x_1} \underline{E}_i^{-x_2} E_i^{x_3} + \left(e^r_{ij}\right)^{x_1} \underline{E}_j^{-x_2} E_j^{x_3},$$
if there is enough residual energy for a packet, i.e., if $\underline{E}_i - e^t_{ij}\lambda > 0$. The path cost is given by the sum of the link costs.
2. If any of the commodities cannot find a path to its destination then stop. Otherwise continue.
3. Augment $\lambda Q^{(c)}$ on each shortest cost path of its commodity and update the residual energy accordingly.
4. Goto 1.

The only change necessary from the above description of the algorithm from the constant information generation rates case to the case of arbitrary information generation processes is that, instead of $\lambda Q^{(c)}$ of flow, all packets generated in between the routing information updates are assigned the available shortest cost path.

4 Performance Comparison through Simulation

4.1 Constant Information Generation Rates

In this section, we evaluate the proposed algorithm for constant information generation rates by comparing the network lifetime achieved with the optimal network lifetime obtained by the linear programming problem solution. Let R_X denote the ratio between the network lifetime of algorithm X and the optimal solution and be called the *normalized network lifetime*.

Comparison is made with other existing algorithms as well. Other algorithms used in comparison are the minimum total energy (MTE), minimum hop (MH) routing, max-min residual energy (MMRE) routing, CMMBCR, and *max-min* zP_{min}. It has been shown in [4] that MTE can perform arbitrarily bad, and in [5] that the minimum hop (MH) routing can perform arbitrarily bad in the worst case. It should be noted that the network lifetime obtained by MTE is not just the time of first node death. In our simulation, we used FA$(1, 0, 0)$ for MTE and this means the minimum total energy path is used only if there is enough residual energy to support the traffic until the next routing information update. The opposite would be to route the traffic to the minimum total energy path regardless of the residual energy levels. The MMRE routing selects the path whose minimum residual energy fraction after the flow augmentation is the maximum, and is in fact a simpler version of the maximum residual energy path (MREP)[4] where not only the minimum but also all the other nodes' residual energy fraction is compared. The performance of MMRE is slightly worse than that of MMRE [6], and we will not compare with MREP here.

Let there be 20 nodes randomly distributed in a square of 50 m by 50 m. Assume that the transmission range of each node is limited by 25 m, i.e., $j \in S_i$ if and only if $d_{ij} \leq 25$, where d_{ij} is the distance between node i and node j. The energy expenditure per unit information transmission from node i to j is assumed to be

$$e_{ij}^t = e^T + \epsilon_{amp}\ d_{ij}^4, \tag{11}$$

and

$$e_{ij}^r = e^R, \tag{12}$$

where $e^T = 50$ nJ/bit and $e^R = 150$ nJ/bit are the energy consumed in the transceiver circuitry at the transmitter and the receiver respectively, and $\epsilon_{amp} = 100$ pJ/bit/m^4 is the energy consumed at the output transmitter antenna for transmitting one meter. We have slightly modified the communication energy consumption model used in [12]. The receiver circuitry is in general more complex and consumes more energy than the transmitter circuitry within the same order of magnitude. The path loss exponent of four is chosen to account for the multipath reflection instead of using a free space model which uses two. However, it should be emphasized that the specific energy consumption model is used for the simulation and does not invalidate our problem formulation nor the proposed algorithm. Note that there may be cases where no path is available between an origin and the destination, although it was very rare. We simply discarded these cases to ensure the connectivity.

For the shortest cost path computation, we used centralized Bellman-Ford algorithm in the simulation and assumed that the residual energy levels are updated and the shortest cost path computation is completed within the routing information update interval. The energy consumed in the communication of routing control packets and in the shortest cost path computation is ignored in the simulation.

Two different cases are simulated: i) single commodity case where information generated at a randomly selected origin node needs to reach a destination node located at $(45, 45)$; ii) multicommodity case where each of the five origin nodes has its own single designated destination node.

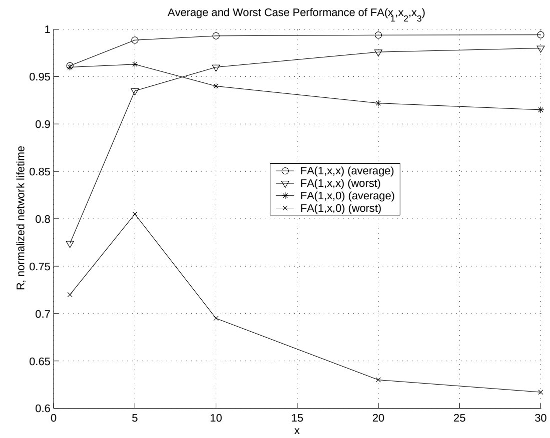


Figure 4: Performance of FA$(1, x, x)$ is compared with FA$(1, x, 0)$.

First of all, algorithm FA(x_1, x_2, x_3) is simulated to find the best parameters x_1, x_2, and x_3 in the single commodity case. Multicommodity case results are not shown here since they were similar to the single commodity case. Let node i have initial energy of $E_i = 10$ J if i is even and $E_i = 20$ J if i is odd. Note that this unequal initial energy levels are used only in this experiment in order to determine whether normalized residual energy or the absolute residual energy should be used, and in the other experiments all nodes have the same initial energy levels. The information generation rate at the origin node o is $Q_o = 1$, and the augmentation step size of $\lambda = 5000$ bits was used. We have experimented with one hundred randomly generated networks.

In Figure 4, comparison is made between FA$(1, x, x)$ and FA$(1, x, 0)$ in order to determine whether the normalized residual energy or the absolute residual energy should be used. From the figure it is obvious that the normalized residual energy should be used.

In Figure 5, comparison is made between FA$(1, x, x)$ and FA$(0, x, x)$ in order to determine whether the communication energy consumption should be included in the link cost. From the figure one can observe that whether the communication energy consumption term is included or not makes a significant difference in the network lifetime. Recall that MTE and MH corresponds to FA$(1, 0, 0)$ and FA$(0, 0, 0)$ respectively and note their performance.

From this experiment we could observe that in all cases, FA$(1, x, x)$ was the best in both the average and the worst case performance. Therefore, in the rest of the paper only FA$(1, x, x)$ will be treated.

Figures 6 and 7 plot the average and the worst case performance of algorithm FA$(1, x, x)$ for various values of λ. Note that $\lambda = 5000$ bits in our model can be interpreted as having the routing information update every ten packets of size 500 bits. We could observe that as the augmentation step size λ became larger, the performance deteriorated. This phenomenon is natural and was expected because the larger λ means less frequent updates on the routing information, i.e., the normalized residual energy level. The curves corresponding to $\lambda = 5000$ showed monotonic in-

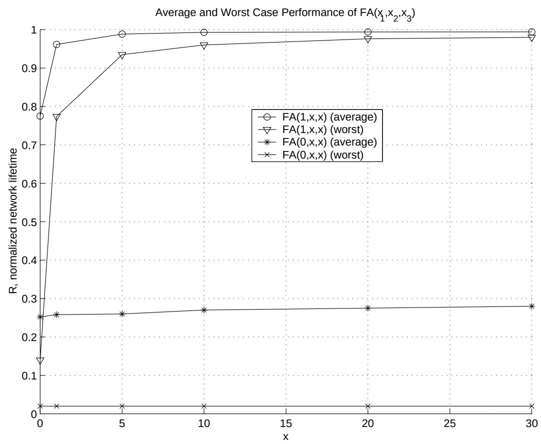


Figure 5: Performance of $\text{FA}(1, x, x)$ is compared with $\text{FA}(0, x, x)$.

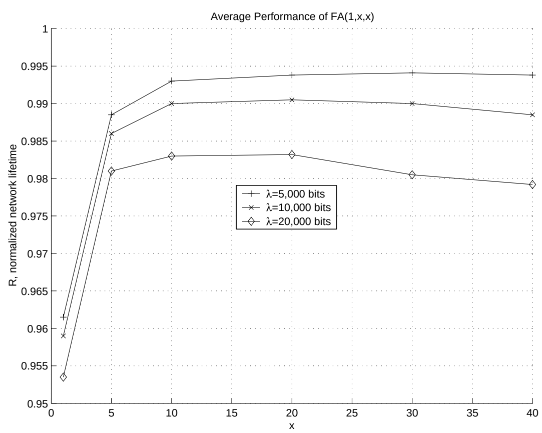


Figure 6: The average performance of $\text{FA}(1, x, x)$ for various values of λ.

crease as x was increased. This means that it is better to have a steeper curve for the residual energy term. Note, however, that for larger λ the curves are monotonically increasing only up to a certain point. We could observe that there is an optimal parameter x for a given λ. The optimal parameter x also depends on the initial energy level, communication energy consumption model, network size or density. At this point, unfortunately, we don't know exactly how to calculate in advance the optimal value of x.

Before comparing all the algorithms, let's compare the algorithm FA with MTE by an example graph, where the origin node is given by $O = \{1\}$ and the destination node is given by $D = \{20\}$. Figures 8 and 9 show the solutions of MTE and $\text{FA}(1, 30, 30)$, respectively. The true optimum is $T_{sys}^{opt} = 10256.4$. One can observe that the routes of FA is more spread out than that of MTE. The system lifetime obtained by $\text{FA}(1, 30, 30)$ was 10070, which is more than five times as long as 1900 of MTE in this example and was very close to the optimal. This is a typical example of why the new problem formulation and the new routing algorithms were needed instead of using the existing MTE

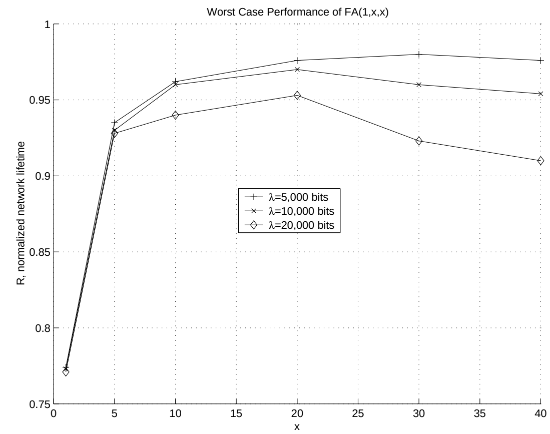


Figure 7: The worst case performance of $\text{FA}(1, x, x)$ for various values of λ.

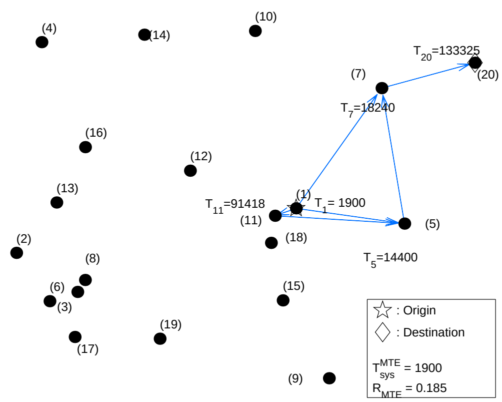


Figure 8: An example showing the solution by MTE for single commodity case where node 1 is the origin node and node 20 is the destination node.

routing.

Now, let's compare the performance of FA with other algorithms. Let each node i have initial energy of $E_i = 10$

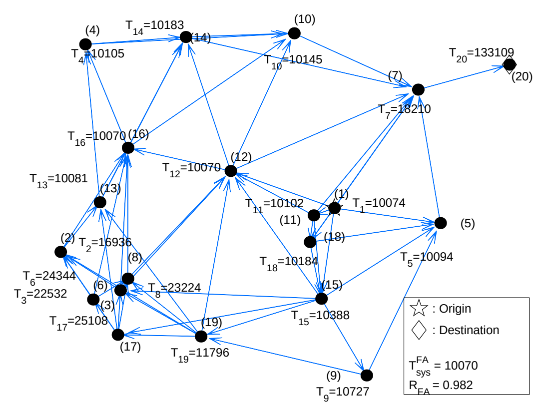


Figure 9: An example showing the solution by $\text{FA}(1, 30, 30)$ for single commodity case where node 1 is the origin node and node 20 is the destination node.

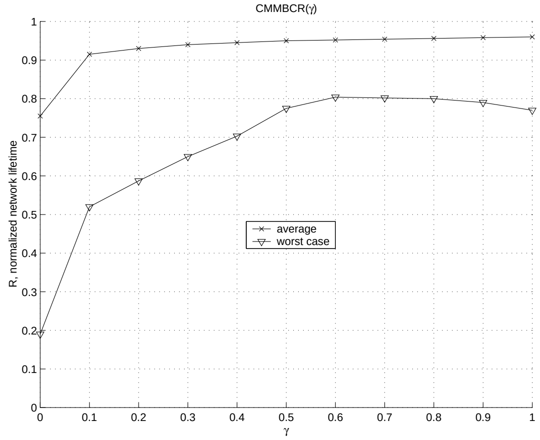


Figure 10: Normalized network lifetime of CMMBCR versus its parameter γ is shown.

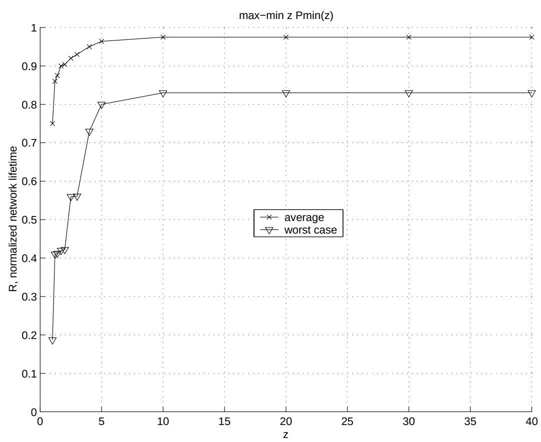


Figure 11: Normalized network lifetime of *max-min* zP_{min} versus its parameter z is shown.

J. The information generation rate at the origin node o is $Q_o = 1$, and the augmentation step size of $\lambda = 5000$ bits was used. We have experimented with one hundred randomly generated networks.

The normalized network lifetime obtained by CMMBCR is depicted in Figure 10 versus its parameter γ, and *max-min* zP_{min}'s result is depicted in Figure 11 versus its parameter z. Finally, Figure 12 shows the performance of FA$(1, x, x)$ versus x. It is interesting to note that algorithms CMMBCR and *max-min* zP_{min} have one design philosophy in common, which is to combine the benefits of MTE and MMRE by varying its parameter value. In CMMBCR, when $\gamma = 0$ it corresponds to MTE and when $\gamma = 1$ it corresponds to MMRE. In *max-min* zP_{min}, when $z = 1$ it corresponds to MTE and when $z = \infty$ it is almost like MMRE but not exactly.

All the algorithms are compared in Table 2 and in Figure 13, where the average and the worst case normalized network lifetime are shown. For each algorithm a total of a hundred randomly generated graphs were simulated, and $\lambda = 5000$ bits was used. The results of CMMBCR and *max-min* zP_{min} depend on its parameter values γ and z

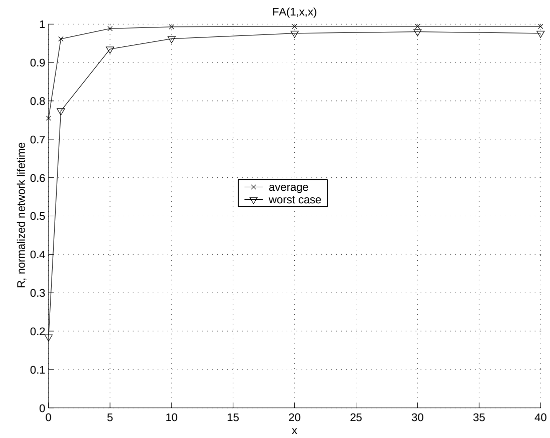


Figure 12: Normalized network lifetime of FA$(1, x, x)$ versus its parameter x is shown.

Table 2: Performance comparison of the algorithms in the single commodity case.

Algorithm X	*avg* R_X	*min* R_X	$Pr\{R_X > 0.9\}$
MTE	0.7576	0.1853	37%
MMRE	0.9569	0.7626	86%
CMMBCR	0.9721	0.8093	97%
max-min zP_{min}	0.9774	0.8465	96%
FA$(1, 1, 1)$	0.9613	0.7716	87%
FA$(1, 30, 30)$	0.9943	0.9816	100%

respectively, but results shown here are obtained by choosing the best parameter value for each instance. While the average of R_{MTE} was about 0.7576, the average system lifetime of all other algorithms were above 0.95 of the optimum. The worst case of R_{MTE} was 0.1853. While R_{MTE} was over 0.9 in only 37 % of the case, the other algorithms were so in 85 % or more of the case. The average gain in the system lifetime obtained by FA$(1, 30, 30)$ was about 50 % compared with MTE. Although both CMMBCR and *max-min* zP_{min} were much better than MTE, they weren't quite as good as FA. Note that $R_{FA(1,30,30)}$ was always over 0.98, i.e., including the worst case. Furthermore, these two algorithms require some type of centralized cooordination while FA does not. In CMMBCR, at the beginning MTE path is used until there is no more available path when all nodes have to convert to calculating MMRE path. In *max-min* zP_{min}, shortest cost path calculation has to be done several times on a number of reduced subgraphs for routing one packet, which is too complex.

In the multicommodity case, commodity $i \in C$ where $C = \{1, 2, 3, 4, 5\}$ is generated at node i and its destination node is node $i + 15$ among 20 randomly distributed nodes. Let each node i have initial energy of $E_i = 10$ J. The information generation rate at each origin node $o \in \{1, 2, 3, 4, 5\}$ is $Q_o = 1$, and the augmentation step size of $\lambda = 5000$ bits was used. We have experimented with one hundred randomly generated networks.

Figures 14 and 15 show examples of multicommodity

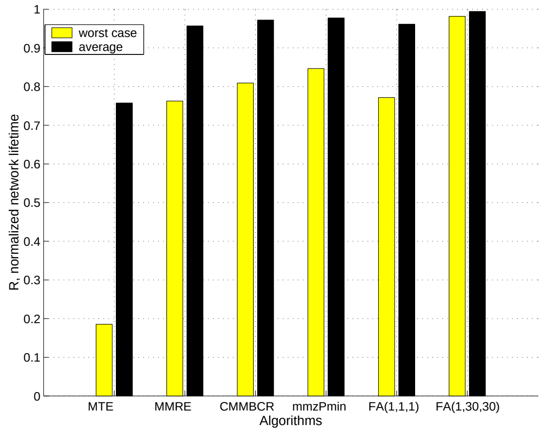


Figure 13: Comparison of average and the worst case performances of algorithms are made in the single commodity case.

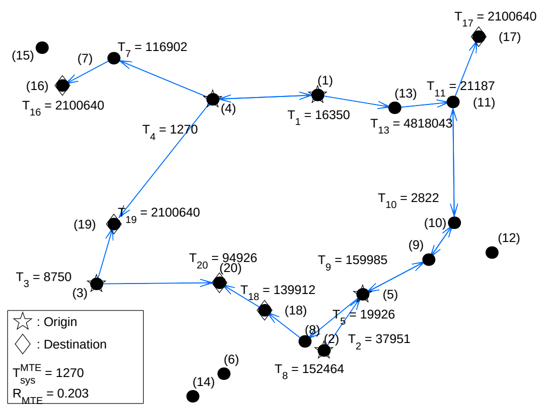


Figure 14: An example showing the solution by MTE for multicommodity case where nodes 1 through 5 are the origin nodes and nodes 16 through 20 are the corresponding destination nodes, respectively.

case solutions by MTE and FA$(1, 10, 10)$ with $\lambda = 5000$ bits respectively, where only the aggregate flows are depicted. In this example, the optimal system lifetime is $T_{sys}^{opt} = 6248.9$, and the system lifetime obtained by FA$(1, 10, 10)$ was 6100, which is more than four times as long as 1270 of MTE and was very close to the optimum.

The performances of the algorithms given in Table 3 and Figure 16 showed similar behavior to the single commodity case. Note that $R_{FA(1,10,10)}$ was the best and $R_{FA(1,10,10)}$ was always over 0.95 of the optimal, i.e., including the worst case. The average gain in the system lifetime obtained by FA$(1, 10, 10)$ was about 78 % longer than that of MTE.

4.2 Arbitrary Information Generation Processes

In this typical scenario, we assume that 100 sensors are uniformly distributed in a square region of 100 m by 100

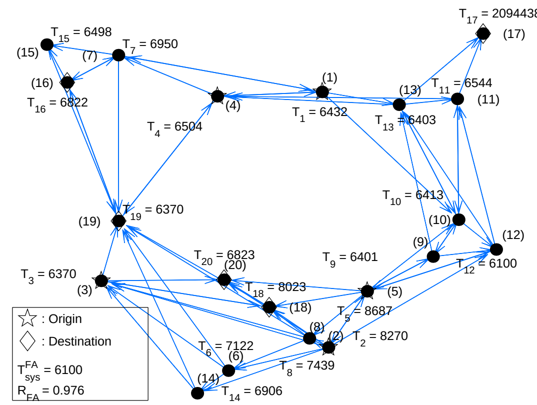


Figure 15: An example showing the solution by FA$(1, 10, 10)$ when $\lambda = 5000$ for multicommodity case where nodes 1 through 5 are the origin nodes and nodes 16 through 20 are the corresponding destination nodes, respectively.

Table 3: Performance comparison of the algorithms in the multicommodity case.

Algorithm X	$avg\ R_X$	$min\ R_X$	$Pr\{R_X > 0.9\}$
MTE	0.6324	0.2032	17%
MMRE	0.9071	0.7069	49%
FA$(1, 1, 1)$	0.9549	0.7758	88%
FA$(1, 10, 10)$	0.9828	0.9517	100%

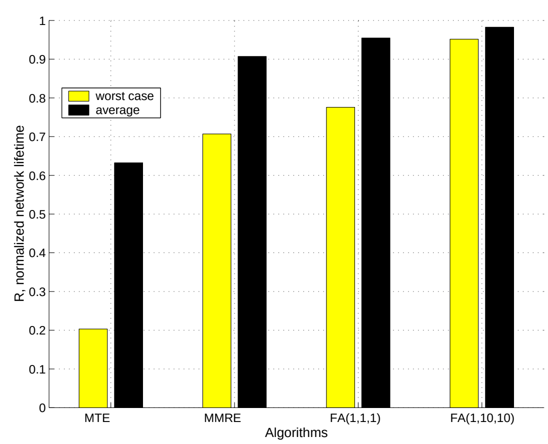


Figure 16: Comparison of average and the worst case performances of the algorithms are made in the multicommodity case.

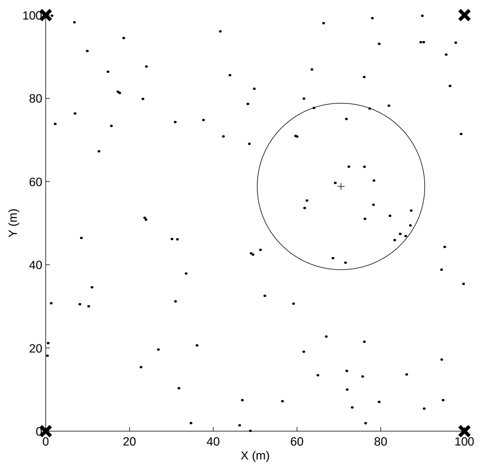


Figure 17: An instance of an example scenario is depicted where '+' is a target, 'x' is a gateway, and '·' is a sensor.

m. A target object passes through the region with the constant speed of 4 m/sec in a randomly chosen direction. Each sensor generates a packet per second while the target is within its sensor range. The generated packets are to be routed to any one of four gateway nodes located on the four corners of the square region. An instance of the scenario is depicted in Figure 17. The sensors in the circle detect the target, where the sensor range is assumed to be limited by 20 m. We also assume that the maximum transmission range is 20 m. Each sensor has the initial energy of 20 J, and the energy consumption model in (11) and (12) was used again. The packet size was 500 bits and the augmentation step size was $\lambda = 5000$ bits.

We generated a new target on any randomly chosen edge of the region as soon as a target moves out of the region. We assume that the energy consumed while there is no target is negligible. We measure the time until the first failure of target detection report to the gateways due to battery outage, and this system lifetime is used as the performance measure. One hundred instances were simulated.

For the optimal solution, we could solve the feasibility version of the integer program iteratively but it is much time-consuming. Therefore, instead of the integer programming problem we use the corresponding linear programming problem, which will yield a slightly looser upper bound. It is known that i) the solution obtained by the linear program is better than or equal to that obtained by the integer program; ii) if the linear program is infeasible then so is the integer program[35].

Table 4 and Figure 18 show the average and the worst case normalized network lifetime obtained by the algorithms. The network lifetime obtained by FA was very close to the optimal network lifetime and was more than three times longer than that of MTE on average.

From the above simulation results, we found out that for some information generation scenarios it is possible to make routing decision on-the-fly and obtain close-to-optimal system lifetime. However, this may not always be the case. Actually, considering the fact that we assume

Table 4: Performance comparison of the algorithms in some arbitrary information generation scenario is shown.

Algorithm X	$avg\ R_X$	$min\ R_X$	$Pr\{R_X > 0.9\}$
MTE	0.3263	0.1151	0%
MMRE	0.8881	0.7707	40%
FA(1, 1, 1)	0.9583	0.8645	99%
FA(1, 5, 5)	0.9669	0.9358	100%

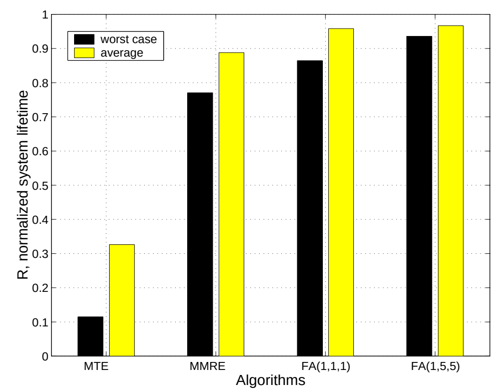
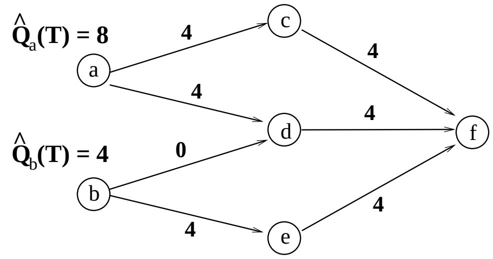


Figure 18: Performance comparison of the algorithms in some arbitrary information generation scenario is shown.

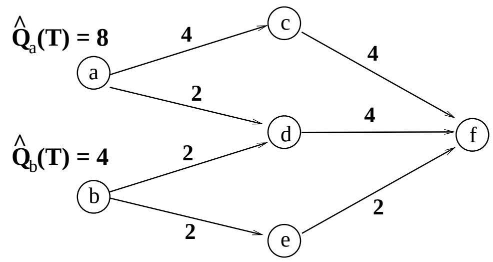
no a priori knowledge about the future information generation process, the simulation results are too good to believe. In the following, we give an example that shows that the performance of the algorithm depends on the information generation sample paths of the process. Consider a network in Figure 19 where each node has 4 units of energy. It requires one unit of energy per packet to cross each link except for two links, $e^t_{ac} = e^t_{ad} = 0.5$. The reception energy consumption is assumed to be zero. If 8 packets are generated at node a before the 4 packets are generated at node b, the algorithm finds the routes as shown in Figure 19 (a) which achieves the optimal system lifetime of 12 time units. However, if 4 packets at node b are generated before the 8 packets at node a, the algorithm will split the traffic generated at node b equally to node d and node e and hence use the energy at node d which should have been dedicated solely to the information generated at node a in order to achieve the optimal system lifetime.

5 Conclusion

In wireless sensor networks where nodes operate on limited battery energy, the efficient utilization of the energy is very important. One of the main characteristics of these networks is that the transmission power consumption is closely coupled with the route selection. The energy efficiency has been considered in wireless ad-hoc network routing, but the conventional routing objective was to minimize the total consumed energy in reaching the destination. In this paper, we have formulated the routing problem as maximizing the network lifetime. The new problem formulation has re-



(a)



(b)

Figure 19: An example network showing that the performance of the algorithm depends on the information generation sample paths. Numbers on the links indicate the number of packets routed through the links. (a) When 8 packets at node a are generated before the 4 packets at node b, the algorithm achieves the optimal system lifetime of 12 time units as shown. (b) When 4 packets at node b are generated before the 8 packets at node a, the system lifetime is 10 time units leaving 2 undeliverable packets at node a.

vealed that the minimum total energy (MTE) routing is not suitable for network-wise optimum utilization of transmission energy. We showed that significant improvement can be made by the newly proposed routing algorithm in terms of maximizing the system lifetime, which can also be interpreted as maximizing the amount of information transfer between the origin and destination nodes given the limited energy. The proposed algorithm is a shortest cost path routing whose link cost is a combination of transmission and reception energy consumption and the residual energy levels at the two end nodes. The simulation results showed close-to-optimal performance most of the time with both the fixed information generation rates and some arbitrary information generation process of a moving target detecting scenario in wireless sensor networks. Future research directions will be to study the effect of network density and quantized residual energy levels on the performance and overhead of the algorithm, to apply the new link metric on the on-demand routing protocols, and to consider medium access layer issues.

References

[1] Dennis J. Baker and Anthony Ephremides, "The architectural organization of a mobile radio network via a distributed algorithm," *IEEE Transactions on Communications*, vol. COM-29, no. 11, pp. 1694–1701, Nov. 1981.

[2] Dimitri Bertsekas and Robert Gallager, *Data Networks*, Prentice-Hall, Inc., 2nd edition, 1987.

[3] Timothy Brown, Qi Zhang, and Hal Gabow, "Maximum Flow Life Curve for a Wireless Ad Hoc Network," in *The ACM Symposium on Mobile Ad Hoc Networking & Computing (MobiHoc 2001)*, Long Beach, CA, USA, Oct. 2001.

[4] J.-H. Chang and L. Tassiulas, "Routing for maximum system lifetime in wireless ad-hoc networks," in *Proceedings of 37-th Annual Allerton Conference on Communication, Control, and Computing*, Monticello, IL, USA, Sept. 1999.

[5] Jae-Hwan Chang and Leandros Tassiulas, "Energy conserving routing in wireless ad-hoc networks," in *Proceedings of IEEE INFOCOM*, Tel Aviv, Israel, Mar. 2000, pp. 22–31.

[6] Jae-Hwan Chang and Leandros Tassiulas, "Maximum lifetime routing in wireless sensor networks," in *Proceedings of the Annual ATIRP Conference*, College Park, MD, USA, Mar. 2000.

[7] Anthony Ephremides, Jeffrey E. Wieselthier, and Dennis J. Baker, "A design concept for reliable mobile radio networks with frequency hopping signaling," *Proceedings of the IEEE*, vol. 75, no. 1, pp. 56–73, Jan. 1987.

[8] M. Ettus, "System capacity, latency, and power consumption in multihop-routed SS-CDMA wireless networks," in *Proceedings of IEEE Radio and Wireless Conference (RAWCON) 98*, Colorado Springs, CO, USA, Aug. 1998, pp. 55–58.

[9] Laura Marie Feeney, "An energy-consumption model for performance analysis of routing protocols for mobile ad hoc networks," *Mobile Networks and Applications*, vol. 6, no. 3, pp. 239–249, June 2001.

[10] R.G. Gallager, P.A. Humblet, and P.M. Spira, "A distributed algorithm for minimum weight spanning trees," Tech. Rep. LIDS-P-906-A, Lab. Inform. Decision Syst., Massachusetts Inst. of Technol., Cambridge, MA, USA, Oct. 1979.

[11] Javier Gomez, Andrew T. Campbell, Mahmoud Naghshineh, and Chatschik Bisdikian, "Power-aware routing in wireless packet networks," in *Proc. 6th IEEE International Workshop on Mobile Multimedia Communications (MOMUC'99)*, San Diego, CA, USA, Nov. 1999.

[12] Wendi Heinzelman, Anantha Chandrakasan, and Hari Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," in *Proc. Hawaiian Int'l Conf. on Systems Science*, Jan. 2000.

[13] Chalermek Intanagonwiwat, Ramesh Govindan, and Deborah Estrin, "Directed diffusion: a scalable and robust communication paradigm for sensor networks," in *ACM/IEEE Intl. Conf. on Mobile Computing and Networking (MobiCom 2000)*, Aug. 2000.

[14] D. Johnson and D. Maltz, "Dynamic source routing

in ad hoc wireless networks," in *Mobile Computing*, Tomasz Imielinski and Hank Korth, Eds., chapter 5, pp. 153–181. Kluwer Academic Publishers, 1996.

[15] Brad Karp and H.T. Kung, ""GPSR: Greedy perimeter stateless routing for wireless networks"," in *ACM/IEEE Intl. Conf. on Mobile Computing and Networking (MobiCom 2000)*, Aug. 2000, pp. 243–254.

[16] Young-Bae Ko and Nitin H. Vaidya, "Location-aided routing (lar) in mobile ad hoc networks," in *ACM/IEEE Intl. Conf. on Mobile Computing and Networking (MobiCom 98)*, Dallas, TX, USA, Oct. 1998, pp. 66–75.

[17] Joanna Kulik, Wendi Rabiner Heinzelman, and Hari Balakrishnan, "Negotiation based protocols for disseminating information in wireless sensor networks," *ACM Wireless Networks*, vol. 8, pp. 169–185, 2000.

[18] Qun Li, Javed Aslam, and Daniela Rus, "Online power-aware routing in wireless ad-hoc networks," in *ACM/IEEE Intl. Conf. on Mobile Computing and Networking (MobiCom 2001)*, Rome, Italy, July 2001.

[19] Xiang-Yang Li, "Algorithmic, geometric and graphs issues in wireless networks," *Wireless Communications and Mobile Computing*, vol. 3, no. 2, pp. 119–140, Mar. 2003.

[20] S. Lindsey, K. Sivalingam, and C.S. Raghavendra, *Power Optimization in Routing Protocols for Wireless and Mobile Networks, in: Handbook of Wireless Networks and Mobile Computing*, John Wiley & Sons, 2002.

[21] Teresa H. Meng and Volkan Rodoplu, "Distributed network protocols for wireless communication," in *Proceedings of the 1998 IEEE International Symposium on Circuits and Systems, ISCAS'98*, Monterey, CA, USA, June 1998, vol. 4, pp. 600–603.

[22] A. Michail and A. Ephremides, "A distributed routing algorithm for supporting connection-oriented service in wireless networks with time-varying connectivity," in *Proceedings Third IEEE Symposium on Computers and Communications, ISCC'98*, Athens, Greece, June 1998, pp. 587–591.

[23] S. Murthy and J.J. Garcia-Luna-Aceves, "An efficient routing protocol for wireless networks," *Journal of Special Topics in Mobile Networks and Applications (MONET)*, vol. 1, no. 2, pp. 183–197, 1996.

[24] Stephen G. Nash and Ariela Sofer, *Linear and Nonlinear Programming*, McGraw-Hill, 1996.

[25] Vincent D. Park and M. Scott Corson, "A highly distributed routing algorithm for mobile wireless networks," in *Proc. IEEE INFOCOM'97*, Kobe, Japan, 1997, pp. 1405–1413.

[26] C. Perkins and P. Bhagwat, "Highly dynamic destination-sequenced distance vector routing (DSDV) for mobile computers," in *ACM SIGCOMM*, London, England, Aug. 1994, pp. 234–244.

[27] S. Ramanathan and Regina Rosales-Hain, "Topology control of multihop wireless networks using transmit power adjustment," in *Proceedings of IEEE INFOCOM*, Tel Aviv, Israel, Mar. 2000.

[28] Volkan Rodoplu and Teresa H. Meng, "Minimum energy mobile wireless networks," in *Proceedings of the 1998 IEEE International Conference on Communications, ICC'98*, Atlanta, GA, USA, June 1998, vol. 3, pp. 1633–1639.

[29] Timothy Shepard, "Decentralized channel management in scalable multihop spread spectrum packet radio networks," Tech. Rep. MIT/LCS/TR-670, Massachusetts Institute of Technology Laboratory for Computer Science, July 1995.

[30] S. Singh, M. Woo, and C.S. Raghavendra, "Power-aware routing in mobile ad hoc networks," in *Proceedings of Fourth Annual ACM/IEEE International Conference on Mobile Computing and Networking*, Dallas, TX, USA, Oct. 1998, pp. 181–190.

[31] Ivan Stojmenovic and Xu Lin, "Power-aware localized routing in wireless networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 12, no. 11, pp. 1122–1133, Nov. 2001.

[32] C.-K. Toh, "Maximum Battery Life Routing to Support Ubiquitous Mobile Computing in Wireless Ad Hoc Networks," *IEEE Communications Magazine*, pp. 138–147, June 2001.

[33] Roger Wattenhofer, Li Li, Paramvir Bahl, and Yi-Min Wang, "Distributed topology control for wireless multihop ad-hoc networks," in *Proceedings of IEEE INFOCOM*, Anchorage, AK, USA, Apr. 2001.

[34] J. Widmer, M. Mauve, H. Hartenstein, and H. Fussler, *Position based routing in ad hoc wireless networks, in: The Handbook of Ad Hoc Wireless Networks*, CRC Press, Dec. 2002.

[35] Laurence A. Wolsey, *Integer Programming*, Wiley, 1998.

[36] Ya Xu, John Heidemann, and Deborah Estrin, "Geography-informed energy conservation for ad hoc routing," in *Proceedings of the ACM/IEEE International Conference on Mobile Computing and Networking*, Rome, Italy, July 2001, pp. 70–84.

Acknowledgment

The authors would like to thank the reviewers for their helpful comments and their thorough review. Their suggestions greatly improved the presentation of the paper.

Jae-Hwan Chang (S'92, M'03) was born in Busan, Korea in 1970. He received his B.S. and M.S. degrees both in electronics engineering from Seoul National University, Seoul, Korea, in 1992 and 1994, respectively, and his Ph.D. degree in electrical and computer engineering from the University of Maryland, College Park in 2003. From 1994 to 1995, he was an engineer for the R&D Center at Modacom Co., Ltd., Seoul, Korea. In 2000, he worked as an intern in Telcordia's Applied Research, Morristown, New Jersey. In 2003, he joined the Telecommunication R&D Center of Samsung Electronics Co., Ltd., Suwon, Korea, where he is currently a senior engineer. His research interests include power control, smart antennas, adaptive modulation and coding, and wireless ad hoc networking.

Leandros Tassiulas (S'89, M'91) was born in 1965, in Katerini, Greece. He obtained the Diploma in Electrical Engineering from the Aristotelian University of Thessaloniki, Thessaloniki, Greece in 1987, and the M.S. and Ph.D. degrees in Electrical Engineering from the University of Maryland, College Park in 1989 and 1991 respectively.

From 1991 to 1995 he was an Assistant Professor in the Department of Electrical Engineering, Polytechnic University, Brooklyn, NY. In 1995 he joined the Department of Electrical Engineering, University of Maryland, College Park, where he is now an Associate Professor. He holds a joint appointment with the Institute for Systems Research and is a member of the Center for Satellite and Hybrid Communication Networks, established by NASA.

His research interests are in the field of computer and communication networks with emphasis on wireless communications (terrestrial and satellite systems) and high-speed network architectures and management, in control and optimization of stochastic systems and in parallel and distributed processing.

Dr. Tassiulas received a National Science Foundation (NSF) Research Initiation Award in 1992, an NSF Faculty Early Career Development Award in 1995 and an Office of Naval Research Young Investigator Award in 1997. He coauthored a paper that got the INFOCOM '94 best paper award.