Energy-efficient Capacity-constrained Routing in Wireless Sensor Networks

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Abstract

A critical issue in the design of routing protocols for wireless sensor networks is the efficient utilization of resources such as scarce bandwidth and limited energy supply. Many routing schemes proposed in the literature try to minimize the energy consumed in routing or maximize the lifetime of the sensor network without taking into consideration limited capacity of wireless links. This can lead to congestion, increased delay, packet losses and ultimately to retransmission of packets, which will waste considerable amount of energy. This paper present a Minimum-cost Capacity-constrained Routing (MCCR) protocol which minimize the total energy consumed in routing while guaranteeing that the total load on each sensor node and on each wireless link does not exceed its capacity. The protocol is derived from polynomial-time minimum-cost flow algorithms. Therefore protocol is simple and scalable.

The paper improves the routing protocol in [1] to incorporate integrality, node capacity and link capacity constraints. This improved protocol is called Maximum Lifetime Capacity-constrained Routing (MLCR). The objective of MLCR protocol is to maximize the time until the first battery drains its energy subject to the node capacity and link capacity constraints. A strongly polynomial time algorithm is proposed for a special case of MLCR problem when the energy consumed in transmission by a sensor node is constant.

Simulation results show that the lifetimes of sensor nodes are longest under MLCR protocol. Periodically rearranging the routes using MCCR protocol to account for the dynamically changing system parameters also achieves performance close to MLCR protocol.

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Index Terms

Sensor networks; Ad-hoc networks; Routing; Maximum Lifetime; Energy efficient; Capacity-constrained

I. INTRODUCTION

Wireless sensor networks, designed to monitor and/or control the surrounding environmental phenomena, have the potential to revolutionize many applications. A sensor network consists of sensor nodes and one or more base stations. Sensor nodes generate, process, and forward data (via intermediate sensor nodes) to base stations. Among the major design challenges in the design of sensor networks is the efficient utilization of resources available to sensor nodes such as scarce bandwidth and limited energy supply. Energy efficiency and bandwidth utilization should be improved at all layers of the communication protocol stack. Addressing these issues at the routing layer is very important due to the significant amount of energy consumed in transmitting high volume of data generated by the sensor nodes.

Routing in sensor networks is significantly different from routing in traditional wireless networks like cellular networks and Mobile Ad-hoc Networks (MANET). The routing algorithms for traditional wireless networks are designed to provide good connectivity, fast route convergence and to avoid congestion under high mobility conditions [2], [3]. Any node can generate data destined for any other node in the network and the data rate can vary significantly. In contrast, sensor nodes in sensor networks are generally stationary. Efficient energy and bandwidth management are necessary to prolong the lifetime of sensor networks. Most of the data traffic flows from the sensor nodes to a base station and is of statistical nature. In many surveillance and monitoring application scenarios, each sensor node generates data at a constant rate.

A. Motivation

The conventional way of routing in sensor networks is to route packets on the minimum-cost (least energy) path from the source to the destination. A minimum-cost shortest path tree (rooted at the base station) connecting all nodes can be constructed to identify the minimum-cost paths from sensor nodes to base stations. Routing the data packets towards the base station on these minimum-cost paths is efficient provided the rate of information generation is low or the channel capacity is sufficiently high. However, if the nodes generate data constantly and capacity is limited[1], then routing data on the minimum-cost paths can overload wireless links close to the base station. Disaster recovery networks such as one reported in [4] have tight bandwidth and energy constraints. A routing protocol that does not take the wireless channel capacity limitation and finite buffer size into consideration might route the packets over highly congested links and paths. This will lead to increase in congestion, increased delay and packet losses, which in turn will cause retransmission of packets thereby increasing energy consumption. The packet retransmissions caused by bottleneck communication links can waste a significant amount of energy and shorten the network lifetime.

This paper presents Minimum-cost Capacity-constrained Routing (MCCR) protocol, which finds routes for transferring data from sensor nodes to base stations while guaranteeing that the load on a channel does not exceed its capacity. The paper improves the routing protocol in [1] to incorporate integrality, node capacity and link capacity constraints. This improved protocol is called Maximum Lifetime Capacity-constrained Routing (MLCR). The objective of MLCR protocol is to maximize the time until the first battery drains its energy subject to the node capacity and link capacity constraints. A strongly polynomial time algorithm is proposed for a special case of MLCR problem when the energy consumed in transmission by a sensor node is constant. Simulations are performed to analyzed the performance of the proposed protocols.

B. Highlights

In the routing protocols proposed in this paper, resource rich base stations are responsible for finding routes. Therefore, system wide floodings to discover new routes are avoided and sensor nodes are spared from maintaining huge routing tables, topology-related information and traffic-states. The routing algorithms proposed in this paper are implemented at one of the base stations and the routes are downloaded at other base stations/sensor nodes. Since the base stations have the global view of the sensor network, routes computed at the base stations are more efficient. Offloading the routing decisions from resource-constrained sensor nodes can help them dedicate their limited resources to running applications.

The running time complexities of proposed algorithms are polynomial. Therefore, the protocols are fast and scalable. These protocols avoid congestion, minimize end-to-end delay and improve QoS by routing the data traffic such that the traffic on a wireless channel does not exceed its capacity.

[1]The IEEE 802.15.4 standard defines the physical layer and medium access control (MAC) sublayer specifications for low data rate wireless connectivity among sensor nodes. As per the standard, there can be as many as 65,536 nodes in the network and the raw data rate can be 20, 40 or 250 Kb/s per node.

II. Related Work

Routing protocols for sensor networks have drawn the attention of many researchers. Chang and Tassiulas [1] define the routing problem as an optimization problem where the objective is to maximize the lifetime of a network (i.e. time until the first battery drains-out). Their model has been extended by Zussman and Segall [4] to account for the nodes processing and transmitting limitations. Our work is closely related to the work of [1] and [4] .

A cluster-based energy-efficient protocol is proposed by Heinzelman, et al. [5] and a minimum-cost forwarding protocol is proposed by Ye, et al. [6]. He, et al. [7] have developed a stateless protocol for real-time communication in sensor networks. Routing with the objective of maximizing the total number of messages successfully carried when the rate of information generation is not known is addressed by Kar et al. [8]. Optimizing the network lifetime when the message sequence is not known is addressed by Li, et al. [9]. Gandham, et al. [10] deploy multiple mobile base stations to prolong the lifetime of sensor networks. Energy-aware routing protocols are reported in [11]–[13]. The protocols discussed in this paper take into consideration the limited capacities of the wireless channels and sensor nodes while making routing decisions.

III. System Model

The following assumptions are made about the system model.

1) A sensor network consists of sensor nodes and base stations.
2) Sensor nodes are deployed in an ad-hoc basis for unattended operation and they are static. (No mobility.)
3) Sensor nodes can estimate and control the rate at which data packets are generated. All the data packets are of the same size. In our model, data aggregation [14] is not considered.
4) Sensor nodes can communicate with other sensor nodes and base stations within their radio transmission range using a MAC protocol. The MAC protocol determines the mean rate at which a sensor node can transmit data to its neighbor over a wireless channel. This rate is the channel capacity.
5) Sensor nodes can dynamically control their radio signal power so as to minimize the energy consumed in communication.
6) Sensor nodes can estimate the energy level of their batteries at any time and estimate the energy consumed in transmitting and receiving one unit of data.
7) Multiple base stations are deployed and their locations are fixed and known a priori.

8) Base stations are responsible for gathering topology information, implementing routing algorithm and distributing routing information to sensor nodes.
9) Base stations have sufficient hardware, sufficient software and constant power supply. All the base stations can communicate with each other without interfering with the rest of the sensor network.
10) All the base stations are homogeneous. Thus, the sensor node can send data packets to any base station.
11) The predominant traffic in the network is data traffic from sensor nodes to base stations.

Properties 5 and 6 are desirable for energy efficiency and are optional in protocols discussed.

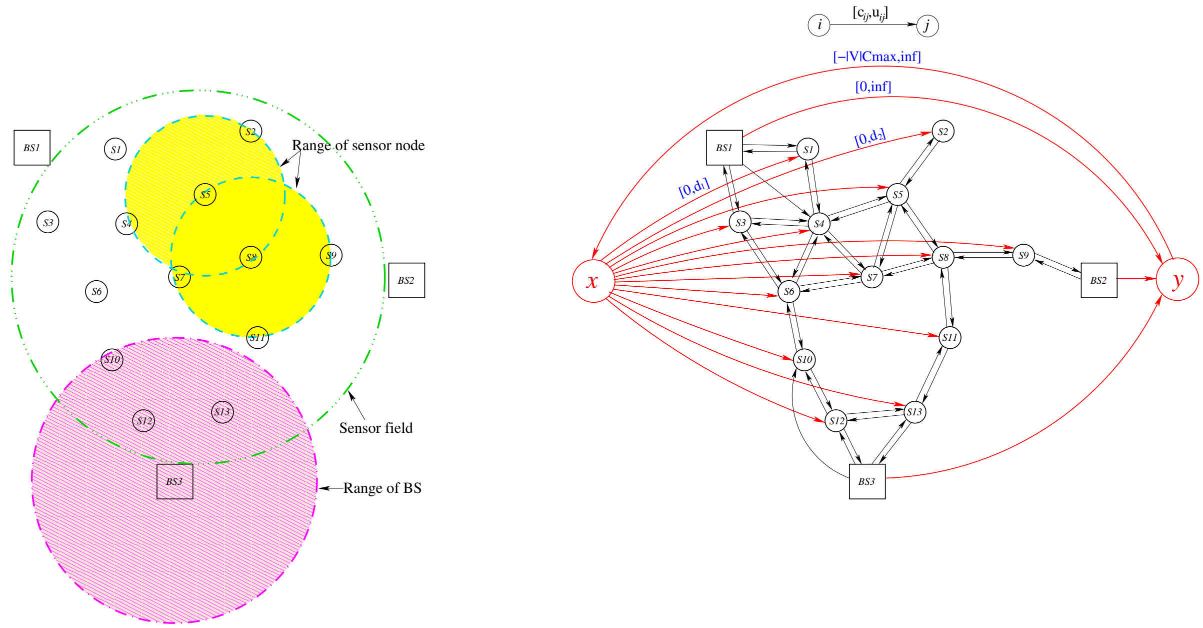
IV. Minimum-cost Capacity-constrained Routing

A. *Problem formulation*

The sensor network under consideration is modeled as a directed graph $G(V, A)$ where
$V = V_s \cup V_b$ where V_s represents the set of sensor nodes and V_b represents the set of base stations.

Let $N_i \subset V$ be the set of nodes, called the *neighbor set* of node i, that can be directly reached by node i in one hop. A is the set of all directed links (i, j) where $i \in V$, $j \in V$ and $j \in N_i$. Each directed link (i, j) has an associated cost per packet C_{ij} and a capacity U_{ij} expressed in number of packets per unit time. Let D_i represent the rate at which the data packets are generated at the sensor node i per unit time. Let C_{max} denote the maximum magnitude of any link cost. Let U_{max} denote the maximum magnitude of any D_i or the maximum magnitude of finite link capacity (whichever is greater). The energy required to transmit one data packet from node i to its neighbor j is represented by T_{ij}. The energy required to receive one data packet at node i from its neighbor j is represented by R_{ij}. It is assumed that only one node, to which the packet is intended, will consume the energy in receiving it. Other nodes, which are neighbors of the transmitter node, will be in the sleep mode or will be communicating with their other neighbors when a packet not destined for them is being transmitted. There is no power consumed by idle listening. The flow of packets from node i to its neighbor j over wireless link (i, j) is represented by f_{ij}. Each sensor node i has an initial battery energy BE_i and a residual battery energy RE_i at a time instant where RE_i is normalized to its initial energy. $0 \leq RE_i \leq 1$.

The objective is to deliver all the data packets generated by sensor nodes to base stations in the most cost-effective manner without exceeding the link capacities. Formally, the problem can be stated as follows.



(a) Deployed Sensor Network

(b) Transformed Graph G'

Fig. 1. Minimum-cost Circulation

$$Obj = Min \sum_{(i,j)\in A} C_{ij} f_{ij}$$

Subject to

$$\sum_{\{j:(i,j)\in A\}} f_{ij} - \sum_{\{j:(j,i)\in A\}} f_{ji} = D_i \qquad \forall i \in V_s, \tag{1a}$$

$$\sum_{\{k:k\in V_b\}} \Big(\sum_{\{j:(k,j)\in A\}} f_{kj} - \sum_{\{j:(j,k)\in A\}} f_{jk} \Big) = - \sum_{\{i:i\in V_s\}} D_i, \tag{1b}$$

$$0 \le f_{ij} \le U_{ij} \qquad \forall (i,j) \in A, \tag{1c}$$

$$f_{ij} \in Z^+ \qquad \forall (i,j) \in A. \tag{1d}$$

The first set of constraints (1a) ensures flow conservation at each sensor node. The second constraint (1b) ensures that base stations receive all the packets generated by all the sensor nodes. The flow of packets on a link must not exceed its capacity and this is ensured by the third set of constraints (1c). The fourth set of constraints (1d) ensures that the (packet) flow values are integers.

Fig. 1a shows an example of a deployed sensor network. The maximum radio range of all the sensor nodes is the same. The radio transmission ranges of sensor nodes 5 and 8, and base station 3 are shown by shaded circles. The radio range of other sensor nodes and other base stations are not shown so as not to clutter the figure. The base stations have a bigger maximum radio range than the sensor nodes. This can lead to unidirectional links from base stations to sensor nodes. The connectivity graph induced by radio transmission ranges of sensor nodes and base stations is shown in Fig. 1b. The additional nodes x and y and links attached to them in Fig. 1b. are explained in the next subsection.

B. Solution

The above defined problem is similar to the *minimum-cost flow* problem, known in the operations research literature [15]. We will convert the above problem into *the minimum-cost circulation* problem as follows (see Fig.1b).

1) Add a super source x, and a super sink y, to the graph $G(V, A)$.
2) Add directed links (x, i), connecting the super source x to sensor node i, for all $i \in V_s$. Set costs of these links to 0 and the capacities to D_i.
3) Add directed links (j, y) connecting the base station j to the super sink y, for all $j \in V_b$. Set costs of these links to 0 and the capacities to infinity.
4) Add a directed link (y, x) connecting the super sink y to the super source x. Set the cost of the link (y, x) to $-|V|C_{max}$ and the capacity to infinity.
5) The modified graph is defined as $G'(V \cup \{x, y\}, A \cup A')$, where $A' = \{(x, i) : i \in V_s\} \cup \{(j, y) : j \in V_b\} \cup \{(y, x)\}$.

The minimum-cost circulation problem can be solved efficiently using well-known minimum-cost flow algorithms [16], [17], [18]. An advantage of the minimum-cost flow algorithm is the integrality of flows. If all link capacities and expected data rates of nodes are integers, then the minimum-cost flow algorithm can find paths with integral flow values.

C. Analysis of the solution

Pushing more flow from x to y will decrease the overall cost of the flow because the link from y back to x has sufficiently large negative cost. It is clear that the maximum flow is bounded from above by $F = D_1 + D_2 + ... + D_{|V_s|}$ because F is the maximum possible flow going out of x, the super source. There are two possibilities that have to be analyzed.

Case 1: $\sum_{\{i:i \in V_s\}} f_{xi} = \sum_{\{i:i \in V_s\}} D_i$

In this case, all the links of the form (x, i), $i \in V_s$ are saturated. The maximum-flow is restricted by the capacities of these links. Consider a link $(x, 1)$ having the capacity D_1. Since all the (x, i) links are saturated, the input flow at node 1 must be $D_1 + \sum_{\{j:(j,1)\in A\}} f_{j1}$ and the output flow must be equal to the input flow (flow conservation). There must be paths from node 1 to base stations which carry the flow $D_1 + \sum_{\{j:(j,1)\in A\}} f_{j1}$. The same argument holds for other nodes.

Case 2: $\sum_{\{i:i\in V_s\}} f_{xi} < \sum_{\{i:i\in V_s\}} D_i$

In this case the maximum flow is restricted by the capacities on the actual links ($(i,j) \in A$) of the network. The minimum-cost flow algorithm will identify the paths from the sensor node i to the base stations which carry the flow D'_i, where $0 \leq D'_i \leq D_i$, $\forall i \in V_s$. The flow on the links (x,i) would be D'_i, $\forall i \in V_s$.

In case 2, the sensor network cannot support the data rate of some nodes. The base station can instruct those nodes to lower their data rates. These nodes are likely in areas which are far away from the base station. This follows from the observation that the packet originating at a longer distance will incur higher cost in reaching the base station. Alternatively, the base station can instruct a few sensor nodes in the densely populated regions to lower their data rates. The intuition behind this idea is that lowering the data rate of some nodes in densely populated areas is better than leaving pockets of areas of the sensor field unattended.

If the channel capacities are infinite then the paths identified by the MCCR are the minimum-cost paths from sensor nodes to their nearest base stations. This is consistent with the conventional minimum-cost routing protocol. In reality, wireless channels have very limited capacity. This might force some packets to take longer paths than the minimum-cost path they would have taken if sufficient capacity was available.

Calculating fairly accurate expected data rate is very important for good performance of the protocol. A sensor node can estimate the expected data rate from the data rates of previous rounds and from the local state of the phenomenon it is observing. A node can periodically piggyback data rate information on data packets. Alternatively, it can be estimated by the base station using the weighted time average of the actual data rate.

D. *Running-time complexity*

The complexity of MCCR protocol is bounded by the complexity of the minimum-cost flow algorithm. Let $|V \cup \{x,y\}| = n$ and $|A \cup A'| = m$. The running time of some of the best known minimum-cost flow algorithms are $O(nmlog(n^2/m)log(nC_{max}))$ [16], $O(nm(loglogU_{max})log(nC_{max}))$ [17] and $O((mlogn)(m + nlogn))$ [18].

E. Load Balancing

The nodes can be prevented from being overloaded by setting a limit on the number of packets a sensor node can handle per unit time. Also, if a contention-based MAC protocol is used, then the nodes have limited capacities. The set of constraints in (2) can be added to ensure that sum of incoming and outgoing packets through a node (sensor or base station) does not exceed its capacity. Let P_i represent the maximum number of packets node i can handle per unit time, called the *node capacity*.

$$\sum_{\{j:(i,j)\in A\}} f_{ij} + \sum_{\{j:(j,i)\in A\}} f_{ji} \leq P_i \quad \forall i \in V. \tag{2}$$

For sensor nodes above equation simplifies to

$$\sum_{\{j:(i,j)\in A\}} f_{ij} \leq (P_i + D_i)/2 \quad \forall i \in V_s.$$

Assuming that base stations are responsible for data gathering the above equation simplifies to

$$\sum_{\{j:(j,i)\in A\}} f_{ji} \leq P_i \quad \forall i \in V_b.$$

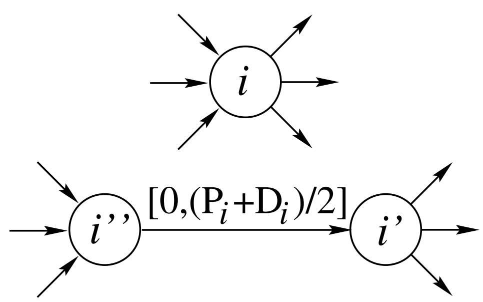


Fig. 2. Node splitting

1) Split each node $i \in V$ into two virtual nodes i' and i'' (Fig.2). The input flow into node i corresponds to the input flow into node i'' and the output flow from node i corresponds to the output flow from node i'.
2) For each link $(i,j) \in A \cup A'$, do the following: Replace (i,j) by a link (i',j'') of the same cost and capacity.
3) Add a link (i'',i') for each $i \in V$.
4) Set the cost of link (i'',i') to zero and capacity to $(P_i{+}D_i)/2$ for each node $i \in V_s$. The information generated by node i is assumed to be generated at node i''.

5) Set the cost of link (i'', i') to zero and capacity to P_i for each node $i \in V_b$.

The above mentioned transformation will cause node i'' to receive all the input flow of node i. The output flow of node i will be sent by the node i'. The link (i'', i') will carry the flow from input to the output which is restricted by its capacity. The appropriate value of P_i will limit the data traffic handled by a node which, in turn, will limit the energy consumed, memory, processing power needed and delay (caused by a node).

V. Maximum Lifetime Routing

Chang and Tassiulas [1] have presented Linear Programming (LP) formulation of energy conserving routing in sensor networks where the performance objective is to maximize the network lifetime (i.e. to maximize the time until the first battery drains-out among all the sensor nodes.)

$$Obj = Max \quad l$$

Subject to

$$\sum_{\{j:(i,j)\in A\}} f_{ij} \cdot l - \sum_{\{j:(j,i)\in A\}} f_{ji} \cdot l = D_i \cdot l \quad \forall i \in V_s, \tag{3a}$$

$$\sum_{\{k:k\in V_b\}} (\sum_{\{j:(k,j)\in A\}} f_{kj} \cdot l - \sum_{\{j:(j,k)\in A\}} f_{jk} \cdot l) = - \sum_{\{i:i\in V_s\}} D_i \cdot l, \tag{3b}$$

$$\sum_{\{j:(i,j)\in A\}} T_{ij} \cdot f_{ij} \cdot l + \sum_{\{j:(j,i)\in A\}} R_{ji} \cdot f_{ji} \cdot l \leq BE_i \quad \forall i \in V_s, \tag{3c}$$

$$0 < l. \tag{3d}$$

The first set of constraints in (3a) ensures flow conservation at each sensor node. The second constraint in (3b) ensures that base stations receive all the packets generated by sensor nodes. The third set of constraints (3c) ensures that the total energy consumed by a sensor node over the lifetime must not exceed total available energy. The constraint in (3d) ensures that the network lifetime is positive. The above problem can be transformed into an LP problem by replacing each occurrence of $f_{ij} \cdot l$ by a new variable $\overline{f_{ij}}$.

Above formulation of MLR problem assumes adaptive transmission power. In adaptive transmission power model, the transmitter is capable of adjusting its transmission power level such that the energy consumed in transmission is minimized while maintaining acceptable signal to noise ratio at the receiver.

In constant transmission power model, the transmitter transmits with the constant transmission power level irrespective of the distance between the transmitter and the intended receiver ($T_{ij} = T_i \;\; \forall j \in N_i$).

The energy consumed in receiving a packet is independent of transmitter ($R_{ji} = R_j \ \forall i \in N_j$). If constant transmission power model is assumed then the MLR problem can be solved efficiently using the max-flow algorithm as follows [1], [4].

Add a super source and a super sink to the graph. Connect the super source to every sensor node i by a directed link whose capacity is $D_i \cdot l$. Connect all the base stations to the super sink by directed links having infinite capacities. Split each sensor node into two sub-nodes and connect them by an internal link. Set the capacity of an internal link to $(BE_i + D_i \cdot l \cdot R_i)/(T_i + R_i)$. Find the maximum flow from super source to super sink in the transformed graph. If the maximum outgoing flow from super source is $\sum_{\{i:i \in V_s\}} D_i \cdot l$ then l is feasible. To find the maximum feasible value of l, a binary search procedure is used. The running time complexity of this procedure is $O(n^3 log L_{max})$ where L_{max} is the maximum possible value of the network lifetime [4].

Note that solving the MLR problem gives the total flow carried by a link ($\overline{f_{ij}}$) during the entire lifetime of the network. Scaling these flow values to the number of packets transmitted over a link per unit time may translate into non-integer values of flow variables. The non-integer values of flow variables can be rounded to integers which results in sub-optimal routing of packets, decreasing the lifetimes of nodes. Alternatively, a packet can be fragmented into multiple packets, but this option is very expensive due to the overheads involved.

In the MLR problem, there are no constraints on the transmission capacities of links and/or nodes. In reality, sensor nodes have very limited transmission capacity and finite size buffers. As per IEEE 802.15.4 standard the raw data rate of a sensor node can be 20, 40 or 250 Kb/s per node. A routing protocol that does not take the wireless channel capacity limitation and finite buffer size into consideration might route the packets over highly congested links and paths. This will lead to increase in congestion, increased delay and packet losses, which in turn will cause retransmission of packets thereby increasing energy consumption.

VI. Maximum Lifetime Capacity-constraint Routing

We extend the above LP formulation of MLR to include channel capacity constraints, node capacity constraints and impose the integrality of the flow values (number of packets transmitted over a link per unit time). In order to linearize constraints, divide both sides of the constraints involving variable l by $l > 0$ and replace $1/l$ with a new variable q. Maximizing the lifetime (l) is equivalent to minimizing q in the transformed problem (MLCR).

$$Obj = Min \quad q$$

Subject to

$$\sum_{\{j:(i,j)\in A\}} f_{ij} - \sum_{\{j:(j,i)\in A\}} f_{ji} = D_i \quad \forall i \in V_s, \tag{4a}$$

$$\sum_{\{k:k\in V_b\}} (\sum_{\{j:(k,j)\in A\}} f_{kj} - \sum_{\{j:(j,k)\in A\}} f_{jk}) = - \sum_{\{i:i\in V_s\}} D_i, \tag{4b}$$

$$\sum_{\{j:(i,j)\in A\}} f_{ij} + \sum_{\{j:(j,i)\in A\}} f_{ji} \leq P_i \quad \forall i \in V, \tag{4c}$$

$$\sum_{\{j:(i,j)\in A\}} T_{ij} \cdot f_{ij} + \sum_{\{j:(j,i)\in A\}} R_{ji} \cdot f_{ji} \leq BE_i \cdot q \quad \forall i \in V_s, \tag{4d}$$

$$0 \leq f_{ij} \leq U_{ij} \qquad \forall (i,j) \in A, \tag{4e}$$

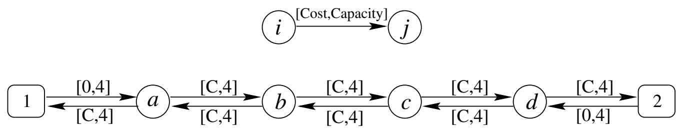
$$0 < q, \tag{4f}$$

$$f_{ij} \in Z^+ \qquad \forall (i,j) \in A. \tag{4g}$$

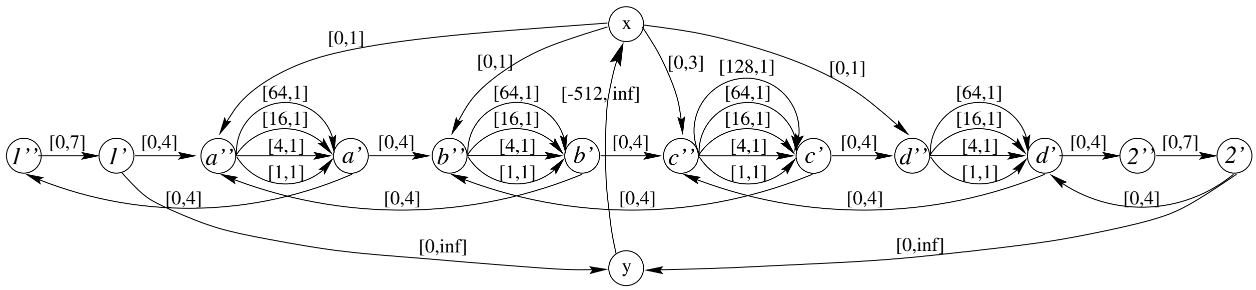
The sum of incoming and outgoing packet flows through a sensor node must not exceed its capacity and this is ensured by the set of constraints in (4c). The set of constraints in (4e) ensure that the flow of packets on a link does not exceed its capacity. The constraints in (4g) ensure that the (packet) flow values are integers.

MLCR adjusts the rate of energy consumption of heavily loaded nodes to values that are proportional to their energy supplies by adjusting the traffic flow over links. If all the sensor nodes have the same amount of energy supplies then the node which consumes the energy at a maximum rate will drain its battery first. To increase the network lifetime, MLCR minimizes the maximum rate of energy consumption (by a node) among all the sensor nodes.

A special case of MLCR problem arises when all the sensor nodes have equal amount of energy supplies ($BE_i = BE \ \forall i \in V_s$) and consume equal amount of power in transmission ($T_i = T \ \forall i \in V_s$). In this case, /minimiz minimizing the maximum flow passing through a node among all the sensor nodes maximizes the lifetime of the network. We propose the following algorithm for this special case of MLCR problem. In is assumed that all link capacities and data rates (packets per unit time) of nodes are integers.



(a) Sample Sensor Network $G(V, A)$



(b) Min-cost Circulation Transformation G'

Fig. 3. Illustrative Example

A. Illustrative Example

We explain the main idea behind our algorithm through a sample network. Consider a network of 4 sensor nodes and 2 base stations as shown in Fig. 3(a). Assume that sensor nodes a, b and d generate 1 packet per unit time each and sensor node c generates 3 packets per unit time. Link capacities of all the links are 4 packets per unit time and the node capacities of all the nodes are 7 units per unit time. Routing packets of a and b towards base station 1 and packets of c and d towards base station 2 consumes the least amount of energy. Under this routing scheme node a transmits 2 packets per unit time and node d transmits 4 packets per unit time. Clearly, lifetime of node d is the least among all the nodes. If node c transmits 2 packets to node d and 1 packet to node b then both nodes a and d have to transmit 3 packets each to base stations 1 and 2 respectively. This result can be obtained by applying minimum-cost circulation algorithm on a transformed network as shown in Fig. 3(b). Thus, MLCR protocol improves the network lifetime by minimizing the maximum-flow passing through a node.

Each node is spilt into 2 nodes (incoming and outgoing) and the corresponding links are rearranged. Add $(7+1)/2 = 4$ parallel directed links, each of unit capacity, between the incoming and outgoing nodes corresponding to nodes a, b and d. The costs of links are set to 1, 4, 16 and 64 respectively. Add $(7+3)/2 = 5$ parallel directed links, each of unit capacity, between the incoming and outgoing nodes corresponding to node c. Set the costs of these links to 1, 4, 16, 64 and 128 respectively. Applying minimum-cost circulation algorithm on the transformed graph provides a solution to the MLCR problem. Under the optimal solution node c transmits 2 packets to node d and 1 packet to node b. Nodes a and d transmit 3 packets each to base stations 1 and 2 respectively.

B. Algorithm

Formally, the algorithm is stated below.

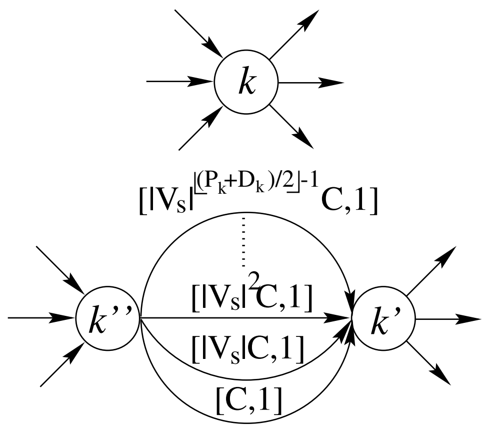


Fig. 4. Node splitting

1) Begin with the network connectivity graph $G(V, A)$.
2) Split each node $k \in V$ into two virtual nodes k' and k''. The input flow into node k corresponds to the input flow into node k'' and the output flow from node k corresponds to the output flow from node k'. The set of nodes V is transformed into new set $V'_s \cup V'_b \cup V''_s \cup V''_b$.
3) For each link $(i, j) \in A$, do the following: Replace (i, j) by a link (i', j'') of the same capacity and zero cost.
4) For each $k \in V_s$ add a total of $\lfloor (P_k + D_k)/2 \rfloor$ parallel directed virtual links connecting two virtual nodes k'' and k' (See Fig.4.). Number these links from 1 to $\lfloor (P_k + D_k)/2 \rfloor$. Set the cost of p^{th} parallel link (k'', k') to $|V_s|^{p-1}C$ and capacity to 1 where C is any arbitrary positive value.
5) For each $k \in V_b$ add a directed virtual link connecting two virtual nodes k'' and k'. Set the cost of the link (k'', k') to zero and capacity to P_k.
6) Add a super source x, and a super sink y, to the graph.
7) Add directed links (x, i''), connecting the super source x to virtual node i'', for all $i'' \in V''_s$. Set costs of these links to 0 and the capacities to D_i.

8) Add directed links (j', y) connecting the virtual node j' to the super sink y, for all $j' \in V_b'$. Set costs of these links to 0 and the capacities to infinity.
9) Add a directed link (y, x) connecting the super sink y to the super source x. Set the cost of the link (y, x) to $-|V_s|^{\lfloor (P_k+D_k)/2 \rfloor} C$ and the capacity to infinity.
10) The modified graph is defined as $G'(V' \cup V'' \cup \{x, y\}, A \cup A')$, where $A' = \{(x, i'') : i'' \in V_s''\} \cup \{(j', y) : j' \in V_b'\} \cup \{(y, x)\} \cup \{(k'', k') : k' \in V', k'' \in V''\}$.
11) Solve the resulting minimum-cost circulation problem using well-known minimum-cost flow algorithms [16], [17], [18].
12) Use the flow values obtained in the previous step to route the flow.

The following definitions applies to the graph transformation described above.

Definition 1: Total flow passing through a sensor node $i \in V_s$ is called the *node load* z_i.

$$z_i = \sum_{\{p=1\}}^{\lfloor (P_k+D_k)/2 \rfloor} f_{k''k'}^{p}$$

.

Note that the lifetime of a sensor node is inversely proportional to the load on the node.

Definition 2: Any directed link on which the flow is strictly less than its capacity ($f_{ij} < U_{ij}$) is called *unsaturated link*.

Any link with positive capacity and zero flow is also an unsaturated link.

Definition 3: A *flow path* is a directed path from the super source to the super sink such that there is a positive flow on each link traversed on that path.

Definition 4: An *alternate path* of a given flow path is a directed path from super source to super sink such that each link traversed on the alternate-path but not traversed on a given flow path, is unsaturated.

Due to the integrality of the flows and capacities, if a link is unsaturated then its residual capacity ($U_{ij} - f_{ij}$) is at least one unit.

Definition 5: The maximum node load among all the sensor nodes traversed on a directed path from super source to super sink is called the *max-path load*.

$$z_{path} = max\{z_i : i \in V_s \wedge i \in Path\}$$

For the following lemma, assume that the optimal flow is found using above mentioned algorithm. Ignore the link (x, y) and corresponding flow. Using flow decomposition theorem [15], the non-negative link flows can be represented as directed path and cycle flows.

Lemma 1: The (directed) path and cycle flow tion decomposition of the optimal flow (between super source and super sink) does not have any directed cycle.

Proof: If flow is optimal then the minimum value of the objective function is reached. Ignore the link (y, x) and corresponding flow. Assume, for contradiction, that the (directed) path and cycle flow decomposition of the optimal flow (between super source and super sink) does have directed cycle(s). Note that all the link costs (except for the link (y, x)) are non-negative. Therefore removing the directed cycle(s) would minimize the objective function value. This contradicts the fact that optimal value of objective function is reached. ■

Theorem 1: The algorithm in VI-B minimizes the value of z^* where $z^* = max\{z_i : i \in V_s\}$.

Proof: Assume that the flow is optimal i.e. the minimum value of the objective function (min-cost circulation) is reached. Note that out of many possible max-flow solutions between super source and super sink, the algorithm finds a solution with the minimum total cost.

We further assume that z^*, found using above algorithm, is not the minimum. Thus, there exists a solution z^0 such that $z^0 = max\{z_i : i \in V_s\}$ and $z^0 < z^*$. Note that the total flow between the super source and the super sink is the same in both solutions. Paths traversed by the flow might be different.

Using the flow decomposition theorem [15], the non-negative link flows can be represented as path and cycle flows. Clearly, the solution z^* does not have any directed cycle between super source and super sink. (See Lemma 1.)

Since z^* is not the minimum, there must be a set of alternate path(s) such that redirecting flows form the flow path(s) having max-path load(s) of z^* to the alternate path(s) would further minimize z^*.

Consider flow path α and alternate path β, having max-path loads of z_α and z_β units respectively. Let $z_\alpha = z^*$. If $z_\alpha - z_\beta < 2$ then redirecting one unit of flow from flow path α to alternate path β does not minimize z_α. Therefore, z_α can be minimized only if $z_\alpha - z_\beta \geq 2$. So assume $z_\alpha - z_\beta \geq 2$.

By definition, the alternate path β never traverses any node with node load greater than z_β units. In an extreme case, flow path α may traverse only one sensor node and the alternate path β may traverse at most $|V_s - 1|$ sensor nodes. Now redirect one unit of flow from flow path α to alternate path β. This decreases the total cost on flow path α by atleaset $|V_s|^{z_\alpha - 1}C$ and increases the total cost on alternate path β by at most $|V_s - 1||V_s|^{z_\beta}C$. Note that $|V_s|^{z_\alpha - 1}C > |V_s - 1||V_s|^{z_\beta}C$ because $z_\alpha - z_\beta \geq 2$. Thus the objective function value decreases. The same argument applies to all other cases and it can be shown for those cases that the objective function values decrease.

This contradicts our initial assumption that the optimum value of the objective function is reached (the flow is optimal). Therefore there does not exist an alternate path that would further minimize the value of z^*. Hence z^* is optimal. ■

C. Computational complexity of the algorithm

Note that the number of links in the transformed (minimum-cost circulation formulation) graph might not be polynomially bounded in $|V|$, $|A|$ and $logU_{max}$. Therefore, polynomial-time algorithms for the minimum-cost flow problem do not translate directly into polynomial-time algorithms for our transformed minimum-cost circulation formulation. However, the above problem can be solved in strictly polynomial time by transforming it into a convex-cost flow problem as follows.

Replace the step 4 of the above algorithm by the following.

For each $k \in V_s$ add a directed virtual link connecting two virtual nodes k'' and k'. The cost of the virtual link is given by $C_{k''k'}(f_{k''k'}) = |V_s|^{f_{k''k'}-1}$. Set the capacity of the virtual link to $(P_k + D_k)/2$.

Clearly, the cost function is a convex function and the resulting problem is a convex-cost flow problem.

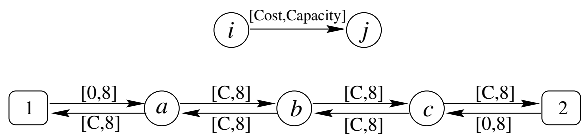
In step 11, solve the resulting convex-cost circulation problem using well-known convex-cost flow algorithms.

The complexity of our algorithm is bounded by the complexity of the convex-cost flow algorithms. The capacity scaling algorithm described in [15] can be applied to obtain an integer optimal flow for a convex-cost flow problem in $O((mlog\ U_{max})S(n, m, C_{max}))$ time where $S(n, m, C_{max})$ is the time required for solving a shortest path problem on a network with n nodes, m arcs, and with C_{max} as the largest link cost.

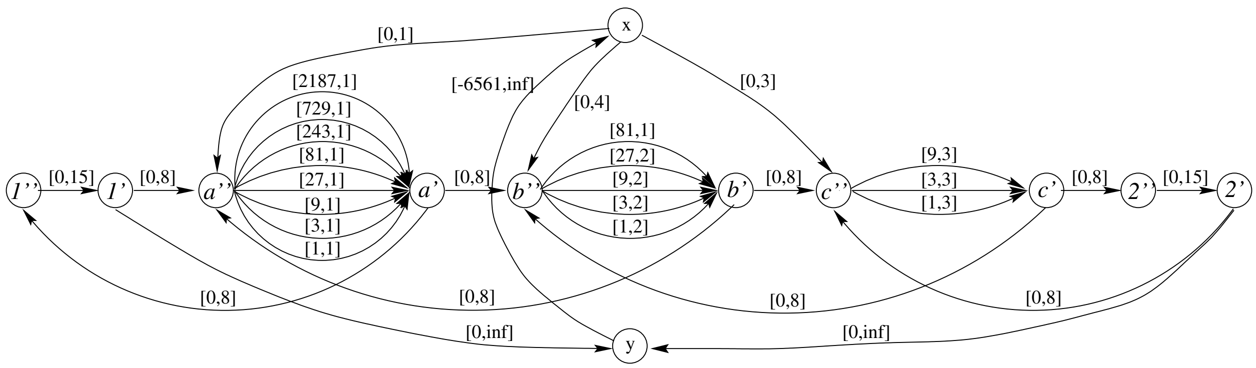
D. Advantages

Our algorithm has several advantages.

1) If all link capacities and expected data rates of sensor nodes are integers, then the convex-cost flow algorithm can find paths with integral flow values.
2) Optimal solution satisfies the link and node capacity constraints.
3) Previously published algorithm in [4] requires $logL_{max}$ iterations of max-flow algorithm which might not be polynomially bounded in the input problem size. Our algorithm finds solution in one iteration of convex-cost flow algorithm and its running time is strictly polynomial if the flow variables are restricted to integers.
4) MLCR problem balances the energy consumption of the most heavily loaded nodes. In general, many different flow arrangements might be possible for lightly loaded nodes. The novel feature of our algorithm is that it also balances the energy consumption of lightly loaded nodes.



(a) Sample Sensor Network $G(V, A)$



(b) Min-cost Circulation Transformation G'

Fig. 5. Algorithm Extensions

E. Extensions

Above mentioned algorithm can be easily extended to the case when sensor nodes have unequal energy supplies and/or constant but unequal transmission power consumption. Consider a sample network as shown in Fig. 5(a). Assume that the energy supplies of nodes a, b and c are 2, 4 and 6 units respectively. Further assume that nodes a, b and c generate 1, 4 and 3 packets per second. Link capacities of all the links are 8 units per unit time and the node capacities of all the nodes are 15 units per unit time. Fig. 5(b) shows the minimum-cost circulation formulation of the problem assuming that all the nodes have equal transmission power consumption. Notice the cost and capacities of the parallel virtual links. The capacities of the parallel virtual links are proportional to the amount of energy supply available to that node. Under the optimal solution, the amount of flow passing through the nodes a, b and c is 2, 4 and 6 units respectively.

The same transformation and solution is valid if all the sensor nodes have equal amount of energy and the power consumed in transmissions by nodes a, b and c is 6, 4 and 2 energy units per unit of information respectively. Note that the capacities of the parallel virtual links are inversely proportional the transmission power consumption of that node. In general the capacities of the parallel virtual links are scaled proportional to the amount of energy supply available and inversely proportional the transmission power consumption.

Note that above algorithm is applicable in case of constant transmission power models. The MLCR problem needs to be solved once in the beginning, and whenever a forwarding node dies thereafter.

VII. Integrality v/s Lifetime

For the same set of input parameters, the network lifetime computed using integer flow values and non-integer flow values can be different with the later being longer than the former. The difference in the lifetimes computed using integer and non-integer flow values depend on the granularity of the time unit.

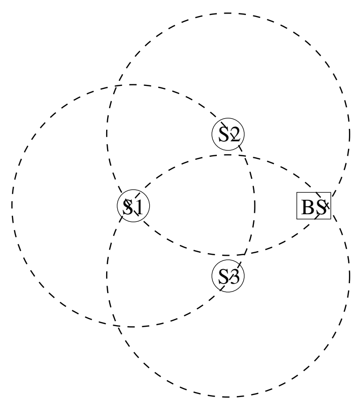


Fig. 6. Integrality v/s Lifetime

Consider three sensor nodes having equal energy supplies, constant and equal transmission power consumption and data rate of 1 packet per time unit as shown in Fig.6. If the flow values are restricted to (integer) packets per time unit then life of the forwarding node (either 2 or 3 whichever is responsible for forwarding the packets of sensor node 1) will be very short compared to the life of non-forwarding nodes. If the flow values are restricted to (integer) packets per *two* time units then lifetimes of nodes 2 and 3 are equal.

If the total flow passing through is a node is very large or equivalently, unit of time under consideration is very big then the impact of integrality on the lifetime is minimal. Thus there is a tradeoff between the integrality and lifetime. Integrality should be imposed on an appropriate unit of time after careful consideration of node capacities and implementation issues.

If integrality of flow values is not required then optimal solution to any desired degree of accuracy can be obtained by above algorithm using a technique known as data scaling. See [15] for more details.

VIII. Maximizing lifetime by rearranging routes

Another way to balance the energy consumption of sensor nodes is to periodically rearrange the flow routes. Recalculated routes should account for the dynamically changing systems parameters such as the residual energy of the sensor nodes. We use the following cost function [1] in MCCR protocol.

$$C_{ij} = (T_{ij} + R_{ji})^{\alpha} / RE_i{}^{\beta} \quad \forall (i,j) \in A$$

Where α and β are non-negative weighting factors. If $\alpha = 1$ and $\beta = 0$, then MCCR protocol will minimize the total energy consumed in routing. If $\beta = 0$, then the minimum-cost circulation problem needs to be solved once in the beginning and whenever a forwarding node dies thereafter. If $\beta \neq 0$, then the minimum-cost circulation problem needs to be solved periodically to account for the residual energy of sensor nodes. Let γ denote the time interval between periodic routing updates.

IX. Communication Cost Model for Simulations

The energy consumed in transmission includes the energy consumed in internal processing (distance independent) and the energy consumed in amplifying the signal to achieve acceptable signal to noise ratio at a receiver (distance dependent). In our work, we assume that the energy consumed in an amplifying the signal to achieve acceptable signal to noise ratio at a receiver is proportional to the square of the distance between transmitter and the intended receiver.

In the adaptive transmission power model used in simulations, energy consumed in transmitting a packet from node i to j is given by [5]

$$T_{ij} = (Size) \times (10.0 + 0.1 \times Dist_{ij}^2) \times 10^{-9} \quad EnergyUnits$$

where $Size$ represents the size of a packet in bits and $Dist_{ij}$ represents actual distance between neighbors i and j in meters.

In the constant transmission energy model used in simulations, the energy consumed in transmitting a packet from node i to j is given by

$$T = (Size) \times (10.0 + 0.1 \times Range^2) \times 10^{-9} \quad EnergyUnits$$

where $Range$ denotes the transmission range of a sensor node in meters.

The cost of receiving a packet is the same in both the models and is given by

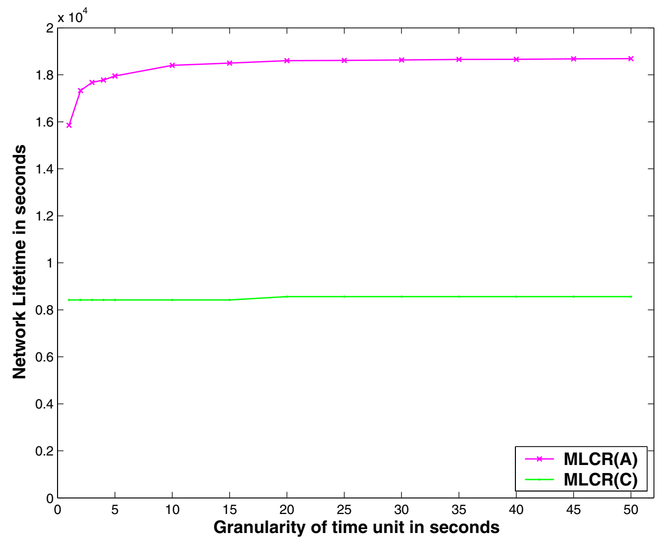


Fig. 7. Integrality v/s Lifetime

$$R = (Size) \times (10.0) \times 10^{-9} \quad EnergyUnits$$

X. Simulation Results

MCCR and MLCR protocols are compared by measuring their performance on randomly generated sensor network topologies. 100 sensor nodes are randomly distributed in a sensor field of size 100 m $\times$ 100 m. Four base stations are deployed on the periphery of the sensor field, one at the midpoint of each side of the square field. The transmission range of each sensor node is 25.0 meters. The transmission range of each base station is 50.0 meters. The routes are computed at one of the base stations and are distributed to the sensor nodes. The size of each data packet is 500 bits and the size of each routing packet is 200 bits. The node capacity of each sensor node is 40.0 Kbps[2] and the link capacity of each wireless link is 10.0 Kbps. The rate of information generation is 1 packet/second. Each sensor node is equipped with initial energy of 1.0 EnergyUnit.

MLCR protocols under constant and adaptive transmission energy models are denoted by MLCR(C) and MLCR(A) respectively. CPLEX® 8.1.0 optimizer [19] is used to solve ILP formulations of MLCR problems. The network lifetime computed using MLCR protocol depends on the granularity of the time unit. Simulation results plotted in Fig. 7 show that the network lifetime is the shortest when the flow

[2]As per the IEEE 802.15.4 standard, the raw data rate of a sensor can be 20, 40 or 250 Kb/s.

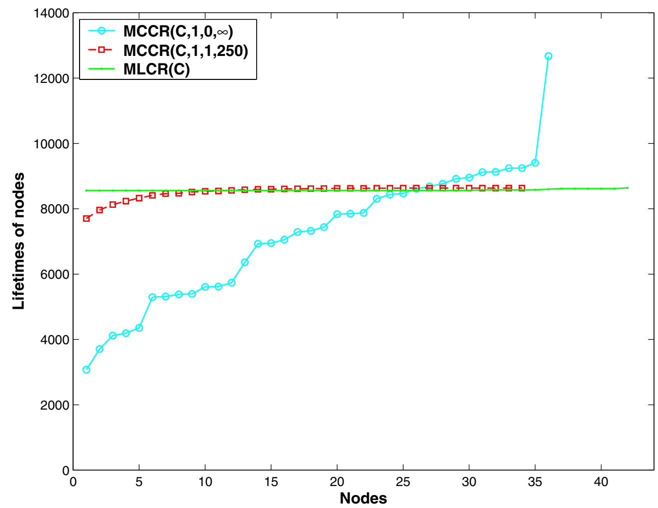


Fig. 8. Lifetimes of sensor nodes

variables are restricted to integers per second. The network lifetime is the longest when the flow variables are unrestricted. The network lifetime is very close to its longest possible value when the granularity of the time unit is 20 seconds. Therefore the granularity of the time unit is set to 20 seconds for the remaining set of simulations.

MCCR problems are solved using an implementation of minimum-cost flow algorithm obtained from [20]. MCCR(C,α,β,γ) and MCCR(A,α,β,γ) denote MCCR protocols under constant and adaptive transmission energy models respectively where the last three parameters inside the parenthesis are input parameters. If $\beta = 0$ then $\gamma = \infty$ which means the routing information is updated only when a sensor node dies. If $\beta \neq 0$ then the routing information is updated when the time elapsed since the last routing update is γ or when a sensor node dies, whichever occurs first. We compare following protocols.

1) MCCR(C,1,0,∞), 2) MCCR(C,1,1,250), 3) MLCR(C) 4) MCCR(A,1,0,∞) 5) MCCR(A,1,1,250) 6) MLCR(A).

Fig.8 and Fig.9 show the time when the batteries of sensor nodes drain-out. Note that the network becomes disconnected when all the sensor nodes which can directly transmit packets to base stations have died. In MLCR(C) and MLCR(A) the lifetimes of individual sensor nodes are close whereas in MCCR(C,1,0,∞) and MCCR(A,1,0,∞) the lifetimes of individual sensor nodes vary significantly. MLCR balances the energy consumed by a few heavily loaded sensor nodes close to base stations by adjusting the flow of packets through them. The flow of packets through lightly loaded sensor nodes can be sub-optimal which significantly increases the total energy consumed in routing. Therefore, in MLBCR, many

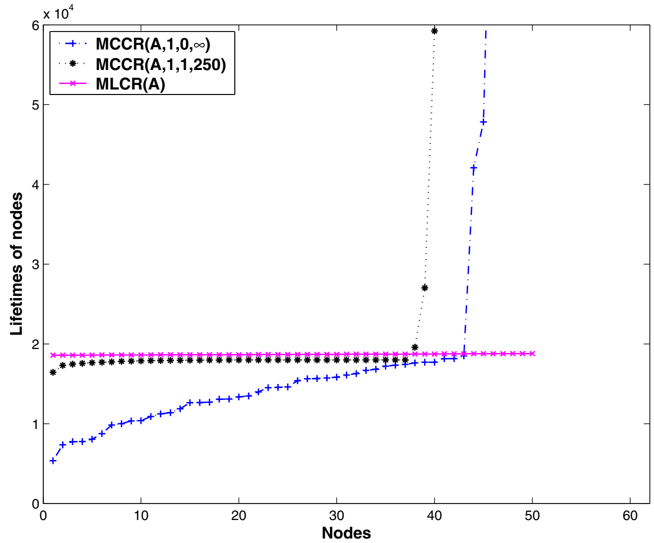


Fig. 9. Lifetimes of sensor nodes

sensor nodes die in a short period of time and the total number of sensor nodes that die when the network becomes completely disconnected is very high, lowering the residual energy of the network as shown in Fig. 10.

MCCR(C,1,0,∞) and MCCR(A,1,0,∞) minimize the total energy consumed in the routing, so heavily loaded nodes die quickly and lightly loaded nodes die very late. MCCR(C,1,1,250) has the highest residual energy and the least number of nodes are dead. In MCCR, a few sensor nodes live a long time compared to most other nodes because they are located in such a position that routing packets of other nodes through them is either very expensive or is not feasible. For example, routing packets through a node located very close to a base station is very expensive because the energy consumed in processing and receiving packets is very high compared to energy saved by an amplifier.

MCCR(C,1,1,250) and MCCR(A,1,1,250) balance the energy consumption by periodically updating routes. As the residual energy of a sensor node decreases, the cost of using outgoing links from that sensor node increases. Note that lifetimes of most sensor nodes in MCCR(C,1,1,250) and in MCCR(A,1,1,250) are very close to those in MLCR(C) and MLCR(A) respectively. Thus, periodically rearranging the routes can significantly enhance the lifetimes of heavily loaded sensor nodes.

Fig. 11 shows the total number of messages received until the network becomes completely disconnected. The number of messages received in the adaptive transmission energy models is more than double the total number of messages received in constant transmission energy models because the lifetimes of

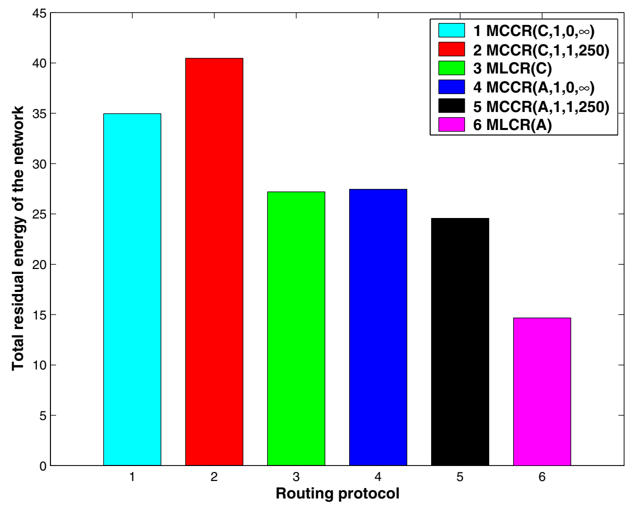


Fig. 10. Residual energy of the network

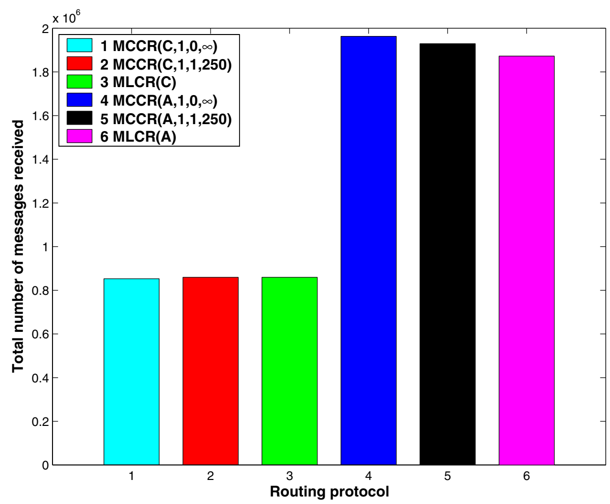


Fig. 11. Total number of messages received

nodes in former are more than double the lifetimes of nodes in later. The total number of messages received in MCCR(C,1,0,∞), MCCR(C,1,1,250) and MLCR(C) are almost the same because the lifetimes of nodes in all the three models are very close. MCCR(A,1,0,∞) receives the highest total number of messages followed by MCCR(A,1,1,250) because in both schemes, a few lightly loaded sensor nodes last a long time.

The lifetimes of nodes in a variable transmission energy model are more than double the lifetimes of nodes in a constant transmission energy model (See Fig.8 and Fig. 9). Clearly, equipping sensor nodes with power control transmitters can significantly increase the lifetimes of sensor nodes. The energy consumed in processing and receiving a packet is independent of the distance between the transmitter and the receiver. Therefore, actual increase in the lifetime depends on the energy saved in an amplifier. In our model, the energy saved by a power control transmitter is proportional to $Range^2 - Dist_{ij}^2$ where $Dist_{ij}$ is the actual distance between neighbors i and j. If the transmission range is increased then the ratio of lifetimes in the variable transmission energy model to lifetimes in the constant transmission energy model should also increase. We compared the lifetimes of nodes in MCCR(A,1,1,250) to the lifetimes of nodes in MCCR(C,1,1,250) when the transmission range of the nodes was increased to 50.0 meters. Simulation results showed that lifetimes of nodes in MCCR(A,1,1,250) were more than three times of those in MCCR(C,1,1,250).

A. Analysis

ILP formulations of MLCR problems are NP-hard to solve. Moreover, ILP formulations of MLCR problems become infeasible if sufficient capacity is not available to support data rates of all the active sensor nodes. The algorithms presented in this paper can solve MLCR(C) and MCCR problems in polynomial time while preserving integrality property. Even if sufficient capacity is not available, the MLCR(C) and MCCR problems can be solved using algorithms presented and the solution can be used to identify nodes whose data rates cannot be supported. Simulation results indicate that MLCR achieves longer lifetimes compared to MCCR in the test network.

Results show that periodically rearranging the routes to account for the dynamically changing system parameters such as the residual energy can greatly enhance the lifetimes of heavily loaded sensor nodes. The energy level of a node can be piggybacked on the data packets to a base station. Alternatively, the base station can calculate the residual energy at sensor nodes based on the estimated energy consumed by a sensor node in sensing, processing and communication.

If each sensor node is in the direct transmission range of at least one of the base stations then periodically rearranging the routes is easy and energy efficient. If source-based routing is used to propagate routing information from base stations to sensor nodes then frequent routing updates can consume a significant amount of energy and reduce the lifetimes of nodes. Thus MCCR protocol with periodic routing updates is useful when system parameters are changing dynamically. MCCR protocol that minimizes the total energy consumption is useful when sensor nodes have replanishable energy supplies.

When a node fails or becomes inoperational, the base station stops receiving data packets from the failed node and all other nodes whose data packets were forwarded by the failed node. The base station can use this information to detect node failures. Alternatively, a node downstream from the failed node can detect the node failure and send the status update message to the base station.

The routing information needs to be updated whenever a forwarding node dies. In MLCR protocol all the nodes which are one hop away from base stations die at the same time and the network becomes disconnected. Therefore, the death of the first node can be considered as the end of the lifetime for the entire network and the routing information need not be updated. Thus, routing overhead is the minimum in the MLCR protocol. Moreover, solving MLCR problem accurately determines the lifetime of the network. For static, finite energy sensor networks the MLCR protocol is very useful.

XI. Conclusion and Future Work

This paper presents algorithms for capacity-constrained minimum-cost and maximum lifetime routing problems in wireless sensor networks. The algorithms are simple, scalable and efficient. Simulation results show that the MLCR protocol gives good performance. The future versions of these protocols will address data aggregation, bandwidth reservation and mobility management issues.

Acknowledgment

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References

[1] J.-H. Chang and L. Tassiulas, "Energy conserving routing in wireless ad-hoc networks," in *Proceedings of IEEE INFOCOM '00*, Tel-Aviv, Israel, Mar. 2000, pp. 22–31.

[2] E. Royer and C. Toh, "A review of current routing protocols for ad-hoc mobile wireless networks," *IEEE Personal Communications*, vol. 6, no. 2, pp. 46–55, Apr. 1999.

[3] J. Broch, D. A. Maltz, D. B. Johnson, Y.-C. Hu, and J. Jetcheva, "A performance comparison of multi-hop wireless ad hoc network routing protocols," in *Proceedings of the 4th Annual ACM/IEEE International Conference on Mobile Computing and Networking (MOBICOM'98)*, Dallas, TX, Oct. 1998, pp. 85–97.

[4] G. Zussman and A. Segall, "Energy efficient routing in ad hoc disaster recovery networks," in *Proceedings of IEEE INFOCOM '03*, San Francisco, Mar. 2003, pp. 682– 691.

[5] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless micro-sensor networks," in *Proceedings of HICSS '00*, Maui, Hawaii, Jan. 2000, pp. 3005 – 3014.

[6] F. Ye, A. Chen, S. Lu, and L. Zhang, "A scalable solution to minimum cost forwarding in large sensor networks," in *Proceedings of IEEE ICCCN '01*, Scottsdale, Arizona, Oct. 2001, pp. 304–309.

[7] T. He, J. Stankovic, C. Lu, and T. Abdelzaher, "Speed: A stateless protocol for real-time communication in sensor networks," in *Proceedings of IEEE ICDCS '03*, Providence, Rhode Island, May 2003, pp. 46–57.

[8] K. Kar, M. Kodialam, T. V. Lakshman, and L. Tassiulas, "Routing for network capacity maximization in energy-constrained ad-hoc networks," in *Proceedings of IEEE INFOCOM '03*, San Francisco, CA, Mar. 2003, pp. 673–681.

[9] Q. Li, J. Aslam, and D. Rus, "Online power-aware routing in wireless ad-hoc networks," in *Proceedings of ACM MobiCom '01*, Itly, July 2001, pp. 97–107.

[10] S. R. Gandham, M. Dawande, R. Prakash, and S. Venkatesan, "Energy efficient schemes for wireless sensor networks with multiple mobile base stations," in *Proceedings of IEEE Globecom '03*, San Francisco, CA, Dec. 2003.

[11] M. Youssef, M. Younis, and K. Arisha, "A constrained shortest-path energy-aware routing algorithm," in *Proceedings of IEEE Wireless Communications and Networking Conference*, Orlando, FL, Mar. 2002, pp. 794–799.

[12] X. Hong, M. Gerla, H. Wang, and L. Clare, "Load balanced, energy-aware communications for mars sensor networks," in *Proceedings of IEEE Aerospace Conference*, Big Sky, Montana, Mar. 2002, pp. 1109–1115.

[13] A. Manjeshwar and D. Agrawal, "TEEN: a routing protocol for enhanced efficiency in wireless sensor networks," in *Proceedings of 15th International Parallel and Distributed Processing Symposium*, San Francisco, CA, 2001, pp. 2009 – 2015.

[14] C. Intanagonwiwat, R. Govindan, and D. Estrin, "Directed diffusion: A scalable and robust communication paradigm for sensor networks," in *Proceedings of the 6th Annual International Conference on Mobile Computing and Networking*, Boston, MA, Aug. 2000, pp. 56–67.

[15] R. Ahuja, T. Magnanti, and J. Orlin, *Network Flows*. New Jersey: Prentice Hall, 1993.

[16] A. V. Goldberg and R. E. Tarjan, "Solving minimum-cost flow problems by successive approximation," *Mathematics of Operations Research*, vol. 15, no. 3, pp. 430–466, 1990.

[17] R. Ahuja, A. Goldberg, J. Orlin, and R. Tarjan, "Finding minimum-cost flows by double scaling," *Mathematical Programming*, vol. 53, pp. 243–266, 1992.

[18] J. Orlin, "A faster strongly polynomial minimum cost flow algorithm," *Operations Research*, vol. 41, no. 2, pp. 338–50, 1993.

[19] *Using the CPLEX callable library*, ILOG Inc., Incline Village, NV, 1997.

[20] A. Loebel. (2000, Jan.) MCF Version 1.2 - A network simplex implementation. Available for academic use free of charge via WWW. [Online]. Available: www.zib.de