Energy-Efficient and MAC-Aware Routing for Data Aggregation in Sensor Networks

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ABSTRACT

Wireless sensor networks consist of many self-organizing and self-coordinating nodes that cooperatively maintain connectivity without any need for wired infrastructure. Because nodes are battery-powered, efficient use of their available energy resources is important. As a result, recent reported routing schemes for wireless networks mainly focus on conserving energy. Even though these schemes generally save power, they do not account for the MAC contention constraints associated with the shared medium. As a result, routing solutions may not be feasible in the sense that the medium will likely not be able to support the data rates.

In this paper, we propose an energy-efficient and MAC-aware routing scheme for data aggregation in sensor networks that (*i*) accounts for MAC contention constraints, and (*ii*) systematically deals with both objectives of maximizing the network lifetime and minimizing the total consumed energy. Through simulations, we demonstrate that the proposed scheme is more likely to result in physically feasible solutions for networks that are infeasible under the reported schemes. We also infer that the rate solutions obtained under the proposed routing scheme are always feasible whereas those obtained under any of the reported schemes may not be feasible. Further, we show that the proposed approach achieves longer network lifetime than the alternative approaches.

Key words: Energy-efficient routing, MAC-aware routing, rate feasibility, wireless sensor networks.

1 INTRODUCTION

Wireless sensor networks are being considered for many military and civilian applications such as target tracking, environmental monitoring, disease transmissions in animals, and smart kindergarten. They are comprised of a large number of low-cost nodes that collaborate to carry out a certain signal processing task. This collaboration typically occurs in the form of information fusion from nodes in the same geographic vicinity to arrive at a consensus decision related to the signal processing task. A local coordinator node in a geographic region gathers the data from the nearby nodes, fuses the information, and arrives at the necessary consensus decisions.

If the local coordinator node is within the transmission range of another node, then the information is directly forwarded to the coordinator. Otherwise, the nodes rely on other intermediate nodes to forward the information to the coordinator. Since the nodes are often battery-powered, energy conservation during information exchange is critical for increasing the lifetime of the network. As a result, energy conservation has been a focus of several recent papers [1–12].

In [1–5], reduction in energy consumption is achieved through in-network processing and data aggregation at intermediate nodes. For instance, in [1], a method called diffusion routing is proposed for collecting information from a set of nodes. Diffusion routing supports in-network processing to reduce the amount of information exchanged and thereby saving energy. Similar advantages of in-network processing are shown in [4]. Reduction in energy is achieved through careful selection of nodes for data aggregation in [2, 5]. An energy-aware medium access protocol for sensor networks is proposed in [13]. A technique called braided multipath routing is proposed in [14] to increase the robustness of information exchange to route failures while conserving energy. By routing through a series of geographic regions instead of a series of nodes, the scheme in [15] allows many nodes to sleep and conserve energy without disrupting the ongoing communications.

Routing schemes have also been developed to suit the energy-constrained wireless ad hoc networks [6–12]. One class of routing schemes is based on finding routes that minimize the total consumed energy [6, 9, 11]. Another class of schemes focuses on maximizing the lifetime of the network by avoiding routes with nodes having the least amount of available energy [12]. Some schemes formulate the routing problem as a linear programming optimization where the objective function is to optimize energy consumption either by minimizing the total used energy or maximizing the time until the first node runs out of energy resources [7, 8]. Even though these reported routing approaches reduce energy consumption, they all ignore the multiple access control (MAC) contention constraints associated with the shared wireless medium. As a result, the number of flows routed through nodes in the same neighborhood may be such that the shared medium may not be able to provide the net data rate required to support these flows. If this happens, the data rate requirements of the traffic flows cannot be satisfied by the network. A primary reason for this discrepancy is that most of the approaches reported in the literature essentially perform network layer optimization without considering the effects of the underlying MAC layer.

In this paper, we propose an energy-efficient and MAC-aware routing approach for data aggregation in sensor networks that (*i*) accounts for MAC contention constraints and (*ii*) systematically deals with both objectives of maximizing the minimum available energy–increasing the lifetime of the network– and minimizing the total energy consumption. Some of the existing solutions, however, deal with both objectives in an ad hoc fashion (e.g., [12]) based on a parameter that the designer must choose in advance. Through simulation results, we illustrate the importance of considering MAC contention constraints into routing formulations and their effects on the feasibility of the routing solutions. We show that the proposed scheme achieves longer network lifetimes than most of the reported approaches. We also show that the proposed routing scheme can be extended to support extra routing features.

This paper is organized as follows. The related work is given in Section 2. In Section 3, we provide the network model. We present the proposed energy-efficient MAC-aware routing approach in Section 4. A performance evaluation of the proposed scheme is presented in Section 5. Section 6 proposes an extension of the proposed scheme to Active-Idle-Sleep mode. Finally, we conclude the paper in Section 7.

2 Related Work

Routing protocols for wireless networks have been the subject of extensive research [16–22]. Generally speaking, these studies focus on the problem of finding and maintaining routes between a pair of nodes despite topology changes due to node mobility. The schemes are evaluated in terms of performance metrics such as routing overhead, latency for route discovery, and packet drop rate. The use of energy consumption as an optimization measure in determining the routes is more recent [6–12, 15, 23–27]. One class of energy aware routing techniques is based on grouping nodes into clusters where each cluster is represented by a clusterhead node [24–26]. Nodes in this class communicate their data to their clusterhead instead of the processing center, and the clusterheads communicate the aggregated data to the processing center. These clustering techniques reduce the overall power consumption since nodes do not need to communicate their data all the way to the processing center which is typically several hops further away from the nodes than the clusterheads. In [24], the authors propose a distributed algorithm to organize nodes of wireless sensor networks into clusters. Another class of energy aware routing algorithms is based on conserving energy by turning off as many nodes as possible while assuring network connectivity for the active nodes [15, 23]. In these techniques, nodes operate in one of the three distinct modes: Active, Idle, or Sleep. Routing algorithms of this class typically require coordination beyond the local neighborhood to decide which nodes should remain in the Active mode at a given time. Such coordination is difficult to achieve without either tight synchronization or considerable message overhead.

A complementary approach to the above two classes is to make efficient use of energy resources available at the nodes in determining the routes. Some schemes minimize the total energy consumed by the nodes in a route for each traffic flow with an overall goal of minimizing the total energy consumption in the network [6, 9, 11]. If the nodes do not adjust their transmit power based on the distance to the intended receiver, then this is akin to minimizing the number of hops. On the other hand, if the nodes adjust their transmit power based on the distance to the receiver, then this approach tends to choose paths with large number of hops [11]. In [6], the energy spent in packet retransmission is also considered in finding routes that minimize the total energy consumed by the nodes. Unfortunately, these approaches do not generally maximize the network lifetime.

Recent papers have focused on finding routes that account for the energy resources available at the nodes [7, 8, 10, 12, 27]. Some of these techniques [10] maximize the lifetime by selecting routes that maximize the total of the remaining energy of nodes forming the routes. Others (e.g., [11, 12]) maximize the lifetime by finding routes that maximize the minimum remaining energy of all nodes among all paths. In [12], the routing scheme switches its objective depending on the amount of energy available at the nodes. If among all possible routes there exists a non-empty set of routes for which the minimum remaining energy of all nodes in the set is above a pre-specified threshold, then a path minimizing the total consumed energy is chosen among the set. If, on the other hand, there is no route for which the minimum remaining energy of all nodes of the route is above the threshold, then the route that maximizes the minimum remaining energy of all nodes forming the path is selected. In [7, 8], a distributed heuristic is proposed for finding routes with an objective of maximizing the time until at least one node exhausts its energy resources. The performance of the heuristic is compared to an "optimal solution" obtained by solving a linear programming problem. The comparison shows that the heuristic often performs well relative to the optimal solution.

In this paper, we will compare the proposed energy-efficient and MAC-aware routing scheme to the following reported routing schemes. We only present a brief description of the schemes. Refer to their original papers for more details.

1. **Min-total energy** [9, 11]: This scheme finds routes that minimize the total energy consumed by all nodes. We assume that nodes do not adjust their transmission power–i.e., they all use the same amount of energy per transmitted bit. Thus, this scheme is equivalent to finding the shortest path.

2. **Max-min** [10, 11]: This approach finds routes that maximize the minimum remaining energy of all nodes constituting the path.

3. **Conditional max-min** [12]: The **Conditional max-min** scheme switches between the **Min-total energy** and the **Max-min** approaches based on the energy level of nodes' batteries. If among all possible routes there exists a set of routes for which the minimum remaining energy of all nodes is above a pre-fixed threshold, then the scheme uses the **Min-total energy** scheme to select a route from that

set. Otherwise, it uses the Max-min scheme to find a route among all possible routes. We use a pre-fixed threshold equal to 50% of the maximal energy capacity of nodes' batteries.

4. Redirect flow [7,8]: To find a route from node n to node m, this scheme first uses the Max-min scheme to find all routes from each of n's neighbor to m. Then, it balances the rate at which n is communicating with m among all those routes so that all the routes have the same lifetime.

3 ROUTING MODEL

We model the wireless sensor network as a directed graph $G = (\mathcal{N}, \mathcal{F})$ of a finite nonempty set $\mathcal{N}$ of nodes and a set $\mathcal{F}$ of flows. Each flow f corresponds to an ordered pair of distinct nodes (n, m) such that m is within n's transmission range—m is a neighbor of n—and n needs to transmit to m. The set $\mathcal{N}$ consists of one coordinator node (CN) and many sensor nodes (SNs). We consider the multiple-sources to single-destination routing model in which data traffic is only generated by SNs and all destined to the CN, and no traffic is generated by the CN. If a SN is not within direct communication range of the CN, then it relies on other SNs to send its relevant information to the CN. We further assume that G is connected; that is, for each node n there exists at least one path (a set of nodes) through which n can communicate with the CN.

4 ROUTING OPTIMIZATION

Consider the wireless network $G = (\mathcal{N}, \mathcal{F})$ defined in Section 3 where each SN $i \in \mathcal{N}$ generates data traffic destined to the CN at a rate of R_i bits per second. Let $B_i(t)$ denote the energy resources available at SN i for network communications at a given time instant t. Also, let ϵ_{ij} denote the energy required to transmit a bit from node i to node j. Let x_{ij} denote the number of bits per second forwarded by node i to a neighboring node j. Given the required rate vector $R = [R_i]_{1 \leq i \leq |\mathcal{N}|}$, we aim at finding a routing solution that minimizes energy consumption. In the remainder of this section, we describe the proposed routing approach.

4.1 Routing Constraints

Independent of the routing objectives, given the required rate vector $R = [R_i]_{1 \leq i \leq |\mathcal{N}|}$, the following set of constraints must be satisfied.

- FLOW BALANCE CONSTRAINTS:

  At each SN, the total outgoing traffic rate must equal the sum of the incoming traffic rate and the traffic generated at the SN. For the CN, the total incoming traffic rate must equal the total traffic generated by all SNs. That is, for each node $i \in \mathcal{N}$,

$$\sum_{j \in \mathcal{N}} x_{ji} + R_i = \sum_{j \in \mathcal{N}} x_{ij} \quad i \neq CN \tag{1}$$

$$\sum_{j \in \mathcal{N}} x_{ji} = \sum_{j \in \mathcal{N}} R_j \quad i = CN \tag{2}$$

$$x_{ij} \geq 0 \quad j \in \mathcal{N} \tag{3}$$

- ENERGY CONSUMPTION CONSTRAINTS:

  If SN i has $B_i(t_0)$ amount of energy at a particular time t_0, then the remaining energy at any future time $t \geq t_0$ must be greater than or equal to zero. That is, for each sensor node i,

$$B_i(t_0) \geq (t - t_0) \sum_{j \in \mathcal{N}} \epsilon_{ij} x_{ij}. \tag{4}$$

  We assume that the CN has an infinite amount of energy.

- MAC CONTENTION CONSTRAINTS:

  The contention constraints on sharing the medium depend on the medium access control (MAC) protocol. For instance, in an IEEE 802.11 MAC protocol [28] based network, if node i is in communication with node j, then all nodes within the same transmission range of i or j cannot communicate. Let Ψ_{ij} denote the set of all ordered pairs of nodes that cannot communicate with each other as long as node i is transmitting to node j. Then, the rate vector $[x_{ij}]_{1\leq i,j\leq|\mathcal{N}|}$ is feasible—i.e., it satisfies the medium access constraints—if for each ordered pair $(i,j) \in \mathcal{N}$ of nodes the following MAC contention constraints hold [29].

$$x_{ij} + \sum_{(p,q)\in\Psi_{ij}} x_{pq} \leq C. \tag{5}$$

C is the maximum rate supported by the wireless medium. Without loss of generality, in the remainder of this paper we will assume that C equals 1.

4.2 Routing Formulation

Let t_0 be the initial time, and T be a time horizon over which the energy aware optimization is performed. The routing problem is to determine the values of x_{ij} subject to constraints (1)–(5) with the following conflicting objectives: (i) maximize the minimum available energy among all nodes at time $t_0 + T$, and (ii) minimize the total consumed energy by all the nodes over the period T. The first objective tends to increase the lifetime of the network [1] since the objective avoids finding routes with nodes having the least amount of available energy. The second objective, on the other hand, tends to conserve the overall energy.

We propose to divide the multiple objective optimization problem into two linear programming problems (LPPs). In the first LPP (LPP-I), the objective function is to maximize the minimum available energy among all nodes subject to constraints (1)–(5). In the second LPP (LPP-II), the objective function is to minimize the total consumed energy by all the nodes subject not only to

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[1] As defined in [7, 12], the lifetime of the network under rate vector x is the amount of time that runs out the first battery.

constraints (1)–(5) but also to maintaining the maximum value of the objective function achieved by solving LPP-I. Thus, the optimal solution of LPP-II is also an optimal solution of LPP-I. The idea here is that there are often multiple optimal solutions to LPP-I which each corresponds to a data rate vector. If this is the case, LPP-II chooses then from among these multiple rate vectors the one that optimizes the objective function of LPP-II. This is illustrated in Example 1.

We introduce a fictitious variable, denoted λ, and add a new set of constraints that ensure that the energy available at each node after the network is operational for T seconds is at least λ. We call these constraints LIFETIME CONSTRAINTS. Formally, the LIFETIME CONSTRAINTS can be written as follows. For every sensor node i,

$$\lambda \leq B_i(t_0) - T \sum_{j \in \mathcal{N}} \epsilon_{ij} x_{ij}. \tag{6}$$

Maximizing λ subject to constraints (1)–(6) can be shown [30] to be equivalent to maximizing the minimum available energy among all nodes at time $t = t_0 + T$ subject to constraints (1)–(5).

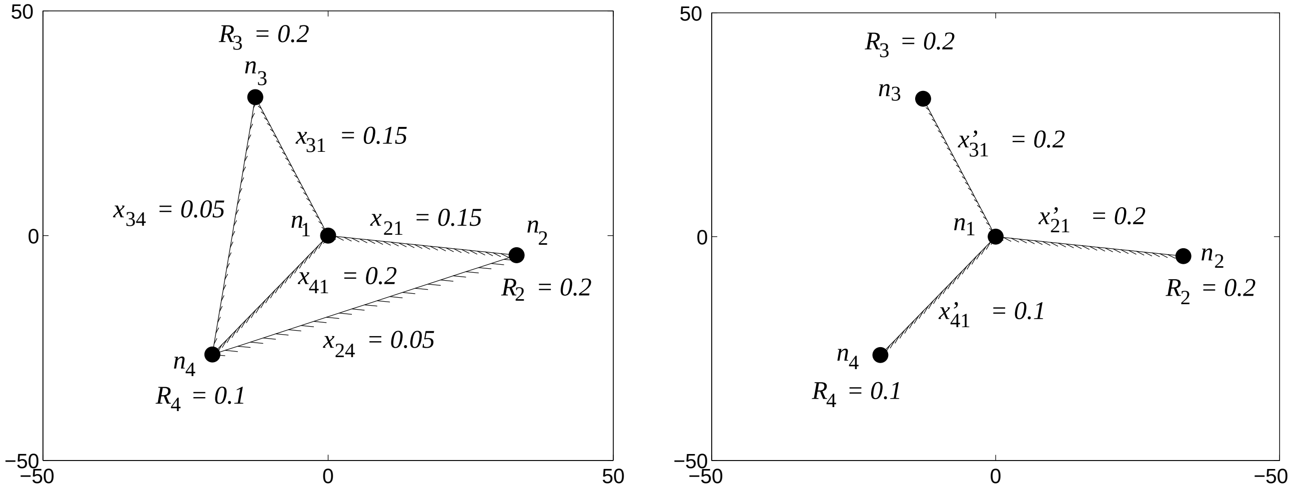
Therefore, LPP-I can be expressed as:

Maximize λ
Subject to:
FLOW BALANCE CONSTRAINTS
ENERGY CONSUMPTION CONSTRAINTS
MAC CONTENTION CONSTRAINTS
LIFETIME CONSTRAINTS

Let λ^* denote the optimal value of λ obtained from solving LPP-I. Then, LPP-II can be stated as:

Maximize $\sum_{j \in \mathcal{N}, j \neq CN} B_j(t_0 + T)$
Subject to:
FLOW BALANCE CONSTRAINTS
ENERGY CONSUMPTION CONSTRAINTS
MAC CONTENTION CONSTRAINTS
$\lambda^* \leq B_i(t_0) - T \sum_{j \in \mathcal{N}} \epsilon_{ij} x_{ij} \quad i \neq CN$

The fourth set of constraints in LPP-II enforces that the minimum available energy at all nodes at



(a) Solution to LPP-I.

(b) Solution to LPP-II.

Figure 1: Rate solutions for Example 1.

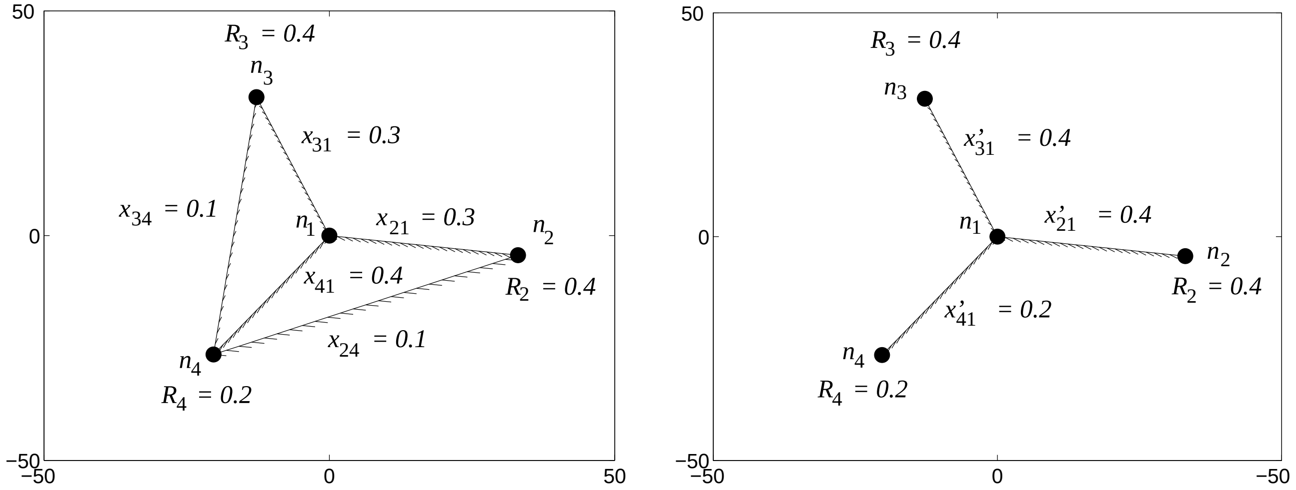
time $t_0 + T$ is above the optimal energy value λ^* determined by LPP-I. In the following example, we illustrate the two-level energy optimization feature of the proposed routing approach.

Example 1: Consider a network of one coordinator node n_1 and three sensor nodes n_2, n_3, and n_4. Assume that all the nodes are neighbors of each other. Suppose that $R_2 = R_3 = 0.2$ and $R_4 = 0.1$ bits per second and all batteries are initially full and all have one Joule worth of energy ($B_2 = B_3 = B_4 = 1$). Also, assume that $\epsilon_{ij} = 0.01$ Joules per bit for all i and j, and the optimization horizon T is one second. The rate vector x, shown in Fig. 1(a), where $x_{21} = x_{31} = 0.15$, $x_{41} = 0.2$, $x_{24} = x_{34} = 0.05$ bits per second and $x_{ij} = 0$ otherwise is a solution obtained by solving LPP-I. The rate solution x' obtained by solving LPP-II is such that $x'_{21} = x'_{31} = 0.2$, $x'_{41} = 0.1$, and $x'_{ij} = 0$ otherwise (see Fig. 1(b)). Note that both x and x' are optimal solutions to LPP-I since they both achieve the same maximal value of λ^* and both result in the maximal network lifetime of 500 seconds. (The value of λ^* depends on the initial energy level of the batteries—for example, at first when all batteries are full, $\lambda^* = 1 - 1 \times 0.01 \times 0.2 = 0.998$ Joule.) However, observe that x' consumes less total energy ($= (0.2{+}0.2{+}0.1) \times 500 \times 0.01 = 2{+}\frac{1}{2}$ Joules) than that consumed by x ($= (0.2{+}0.2{+}0.2) \times 500 \times 0.01 = 3$

Joules). In fact, if we route the traffic using the rate vector x, all nodes simultaneously die after 500 seconds. Alternatively, routing with x' also takes the same amount of time (500 seconds) for the first node to die (nodes n_2 and n_3 die together), but node n_4 will be left with a battery of $\frac{1}{2}$ Joule worth of energy which keeps it alive for another 500 seconds. Thus, the proposed two-level linear programming formulation yields to an optimal solution that balances between a longer lifetime and less overall consumed power—i.e., the formulation minimizes the total consumed energy while maximizing the lifetime. The importance of the two-level energy optimization is studied in greater detail in Subsection 5.2. ■

As mentioned in earlier sections, the proposed routing formulation incorporates MAC contention constraints whereas those reported in the literature (e.g., [7, 8]) do not consider them. If one does not account for the multiple access nature of the wireless medium, the resulting solution may not be feasible [29]. That is, the medium will likely not be able to support the net data rate needed to deal with all the traffic flows routed through some spatial neighborhoods. When this happens, the packet queues at the corresponding nodes will grow and there will be either larger delays or packet losses, both of which result in violation of QoS requirements. We illustrate the importance of including the MAC contention constraints to routing formulations in Example 2.

Example 2: Let us again consider the same network defined in Example 1 where the network consists of one coordinator node n_1 and three sensor nodes n_2, n_3, and n_4. Now, suppose that $R_2 = R_3 = 0.4$ and $R_4 = 0.2$ bits per second and all batteries are again initially full ($B_2 = B_3 = B_4 = 1$). Also, assume that $\epsilon_{ij} = 0.01$ Joules per bit for all i and j. In this example, we solve the routing scheme defined in [7] twice: with and without the MAC contention constraints. Fig. 2(a) shows a solution x obtained by solving the scheme exactly as defined in [7]—i.e., without MAC contention constraints. The rate solution x', shown in Fig. 2(b), is obtained when the MAC contention constraints are included. First, observe that both solutions result in the same maximal lifetime of 250 seconds, thus they both are optimal solutions to the problem formulated in [7]. However, note that the solution obtained without



(a) Without MAC contention constraints.

(b) With MAC contention constraints.

Figure 2: Rate solutions for Example 2.

imposing the MAC contention constraints (Fig. 2(a)) is not physically feasible if IEEE 802.11 [28] is the medium access scheme. This is because the summation of all the rates x_{ij} is equal to 1.2 which exceeds the wireless medium capacity C ($C = 1$). Alternatively, when the MAC contention constraints are included, solving the same problem results in a feasible rate solution ($\sum_{1 \leq i,j \leq 4} x'_{ij} = 1$). This example shows the importance of including the physical contention constraints to routing formulations. In Subsection 5.1, a more detailed illustration is provided. ■

4.3 Routing Implementation

We assume that the CN has an unlimited amount of energy, which is reasonable since typically the CN is connected to an accessible power-supplied infrastructure. Provided that the CN has a reliable power supply, it is responsible for most of the intensive computational processing such as solving the two linear programming problems.

The CN first solves the two linear programming problems, LPP-I and LPP-II. The optimal rate solution x obtained by solving LPP-II is then sent to the sensor nodes. Once a node i receives the rates from the CN, it forwards every packet to its neighbor j with a *packet forwarding probability*, p_{ij}, computed as

$$p_{ij} = \frac{x_{ij}}{\sum_{k \in \mathcal{A}_i} x_{ik}}$$

where $\mathcal{A}_i$ is the set of i's neighbors. This routing process is repeated every T seconds; that is, periodically, the CN solves the routing problem and sends the rates to all the nodes. Nodes use the rate solution to forward packets for the next T seconds. At the end of each optimization horizon T, each node sends its battery level information and its neighbor list to the CN which uses to determine the optimal rates for the next horizon. The value of the optimization horizon T is a design parameter which we will discuss in Subsection 5.2.2.

There are two points worth noting. First, our routing approach assures that the rates provided by the optimal solution are met on the average. The instantaneous rates, however, may deviate considerably from the optimal rates. If T is sufficiently large, then the rates averaged over this horizon are likely to be close to the optimal rates. Second, since all the traffic is going to the CN, packets are forwarded to a given neighbor based only on the forwarding probability and not on the origin of the packets. This works perfectly so long as there is no packet looping during the routing process of the traffic. Packet looping occurs if packets could return to where they came from during the routing process, and results in packets never reaching the CN. The proposition below shows that the solution resulting out of LPP-II is cycle-free [2], and thus the above forwarding scheme ensures that all the packets will reach the CN.

Proposition 1: If x is an optimal solution to LPP-II, then x is cycle-free.

PROOF: We will prove that if x has a cycle then it is not an optimal solution. Let x be a solution that contains at least one cycle. Without loss of generality, let $\mathcal{C} = (1, 2, \ldots, k)$ denote the sequence of

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[2] We use the traditional definition of cycles; i.e., x has a cycle if there exists a sequence $(n_1 n_2 \ldots n_k)$ of nodes in $\mathcal{N}$ such that $x_{k1} > 0$ and $x_{ii+1} > 0$ for $1 \leq i < k$.

nodes forming the cycle. That is, $x_{k1} > 0$ and $x_{ii+1} > 0$ for $1 \leq i < k$. Let $\xi = min\{x_{k1}, min\{x_{ii+1} : i \in \{1, 2, \ldots, k-1\}\}\}$. Consider the vector $[\hat{x}_{ij}]_{1 \leq i,j \leq |\mathcal{N}|}$ such that $\hat{x}_{k1} = x_{k1} - \xi$, $\hat{x}_{ii+1} = x_{ii+1} - \xi$ for $1 \leq i \leq k-1$, and $\hat{x}_{ij} = x_{ij}$ otherwise. Clearly, the objective function value obtained by $\hat{x}$ is greater than that obtained by x since $\xi > 0$. Thus, by showing that $\hat{x}$ satisfies all the constraints stated by LPP-II, we will prove that x is not an optimal solution to LPP-II. Note that each node in $\mathcal{C}$ has both its incoming rate and its outgoing rate reduced by exactly ξ. All other nodes which do not belong to $\mathcal{C}$ have their rates remain the same. Hence, under $\hat{x}$, the FLOW BALANCE CONSTRAINTS are met. Moreover, since for all i, j, $0 < \hat{x}_{ij} \leq x_{ij}$, then $B_i(t_0) \geq (t - t_0) \sum_{j \in \mathcal{N}} \epsilon_{ij} x_{ij} \geq (t - t_0) \sum_{j \in \mathcal{N}} \epsilon_{ij} \hat{x}_{ij}$, and hence, both the ENERGY CONSUMPTION CONSTRAINTS and the LIFETIME CONSTRAINTS are also met. Finally, because $x_{ij} \geq \hat{x}_{ij}$ for all $i, j \in \mathcal{N}$ and x satisfies the MAC CONTENTION CONSTRAINTS, $\hat{x}$ also satisfies these constraints. ■

5 PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed routing scheme. The evaluation consists of two simulation studies. In the first study, we illustrate the effect of MAC contention constraints on the feasibility of the rate solutions; whereas, in the second study, we evaluate the performance of the scheme in terms of network lifetime and energy consumption.

5.1 Effect of MAC Contention Constraints

To further demonstrate the significance of including the MAC contention constraints to routing formulations, we simulate and compare the proposed scheme and all the schemes described in Section 2.

5.1.1 Simulation Method and Metrics

One hundred random wireless sensor networks are generated, each with 50 sensor nodes (SNs) and one coordinator node (CN). The SNs are uniformally distributed in a cell of size 100×100 meters square. The CN is placed in the center of the cell. Each SN is assumed to have data traffic with a rate requirement of $0.01 \times C$ where C is the maximum data rate of the wireless medium. Since there are 50 SNs, this corresponds to an incoming traffic load of 50% at the CN. We consider three values of the transmission range: 21, 25, and 35 meters. For each transmission range, we compute the *average node degree* (δ) which is the average of each node's number of neighbors in all the 100 graphs. These average node degrees are 4.98, 7.53, and 14.65 respectively for the ranges of transmission 21, 25, and 35. All the 100 graphs are connected—i.e., each sensor node is able to communicate with the coordinator node either directly or through a set of nodes.

For each of the three average node degrees δ, we simulate the 100 graphs for the four power aware routing algorithms described in Section 2. We also simulate these graphs using the proposed routing approach, but without including the MAC CONTENTION CONSTRAINTS—i.e., LPP-I and LPP-II are not subject to Eq. (5). Fig. 3 illustrates the effect of not including the MAC contention constraints on the physical feasibility of the solutions obtained by solving the power aware routing schemes. Each bar of the figure corresponds to a combination of a routing scheme and an average node degree, and represents the number of feasible graphs out of the 100 simulated graphs. A simulated graph is considered feasible if the solution obtained by solving the corresponding routing algorithm satisfies the MAC contention constraints [29] given by Eq. (5). Since the aim here is to study the feasibility of the solutions based only on whether they meet the MAC contention constraints, we set a small value for the optimization horizon T so that the ENERGY CONSUMPTION CONSTRAINTS are met and all schemes have rate solutions. We assume that the energy per bit ϵ_{ij} is constant for all nodes, and does not depend on the distance between neighbor nodes.

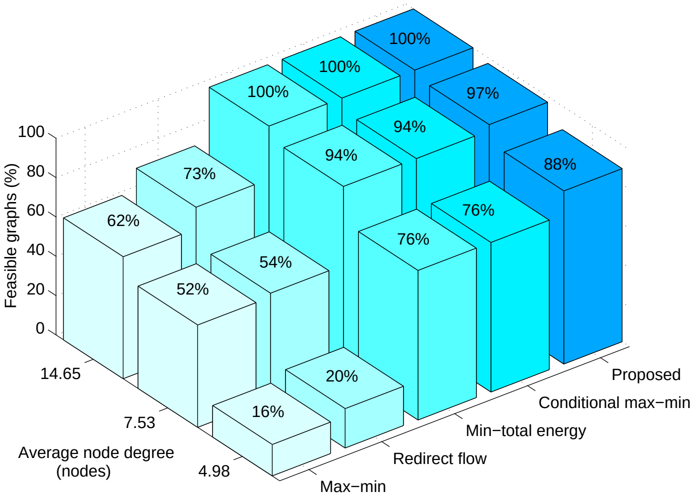

Figure 3: Graph feasibility: Number of SNs = 50, Cell width = 100 meters, Network traffic load = 50%.

5.1.2 Result Analysis

Fig. 3 shows that for each of the five schemes, the higher the average node degree δ, the higher the percentage of feasible graphs. Since, on average, nodes in graphs with higher δ have more neighbors, they have more alternatives for routing. If the average node degree is low, then the likelihood that different nodes are forced to route through the same nodes is higher than if these nodes have more neighbors. Thus, graphs with lower average node degrees result in more physical infeasibility of rate solutions. A second observation we deduce from the figure is that the percentages of feasible solutions obtained by solving the Min-total energy and the Conditional max-min schemes are the same. Since the Conditional max-min scheme is identical to the Min-total energy scheme when battery energy-levels are above a pre-fixed threshold, then for small optimization horizons T, both algorithms result in the same solutions for the first period. In our simulations, the pre-fixed threshold is set to be 50% of the initial battery energy-level. Note that the Max-min approach has the least number of feasible solutions. This is because the scheme tends to choose nodes with maximum remaining energy, and hence nodes with higher energy-levels are more likely to be part of many routes. This in turn increases the chances that some neighborhoods will have higher contention resulting in physical infeasibility of the solution. The

Redirect flow algorithm is similar to the Max-min algorithm except that senders rely on more than one neighbor to forward their traffic, and thus the resulting routes are balanced over more nodes. However, this still results in higher number of infeasible solutions since the distribution is local (at the first hop only), and further nodes in the route will still cause higher contention by being involved in many routes. The Min-total energy scheme does better than the Max-min and the Redirect flow schemes due to the following reason. Since ϵ_{ij} is constant for all nodes, finding routes that minimize the total power is the same as finding the shortest paths—i.e., routes with the least number of hops. For graphs with uniformally distributed nodes, a shortest path algorithm finds routes such that nodes within the same hop-distance from the CN are part of the same number of routes. Thus, the Min-total energy scheme results in routing solutions that are more distributed over all nodes than solutions found by the Max-min and the Redirect flow algorithms. This balances the contention over all neighborhoods resulting then in an increase of the number of feasible graphs. Finally, we observe that the Proposed routing approach performs the best in terms of solution feasibility. In all cases, the Proposed scheme achieves a slightly greater number of feasible graphs than the Min-total energy and the Conditional max-min schemes, and a substantially greater number than the Max-min and the Redirect flow schemes. The key here is that the Proposed formulation finds rates which result in optimal distribution over all the nodes. As in the case of the Min-total energy scheme, an evenly distributed rate solution does better in balancing the physical contention over all neighborhoods. The Proposed approach does better by achieving an optimally balanced contention. However, observe that there are a few graphs for which the solutions obtained by the Proposed scheme are not physically feasible. Out of the 100 graphs, this happens only for 3 and 12 graphs when the average node degrees are respectively 4.98 and 7.53. When nodes do not have many neighbors, including the CN, then the likelihood that nodes must forward their traffic through the same node (usually nodes which are direct neighbors of the CN) is very high. This in turn increases the contention of neighborhoods around the CN. In these cases, the proposed two linear programming formulation does not have a feasible solution.

Given the above, we can make two inferences. First, the proposed scheme is more likely to result in feasible rate solutions for networks that are infeasible under the reported schemes. This is due to the fact that the rate solutions obtained by solving the proposed scheme achieve more balanced contention over all neighborhoods. Second, because the proposed routing formulation accounts for the MAC contention constraints, the rate solutions obtained under it are always feasible whereas those obtained under any of the reported schemes may not be feasible.

5.2 Network Lifetime and Energy Consumption

We evaluate the lifetime performance of the proposed routing scheme by comparing it to the four reported schemes described in Section 2.

5.2.1 Simulation Method and Metrics

Each scheme is simulated for the 16, 52, and 62 out of the 100 graphs that are found feasible in Section 5.1 respectively for the range of transmission values of 21, 25, and 35 meters. Let d denote the transmission range. The average node degrees δ corresponding to these transmission ranges of the 16, 52, and 62 feasible graphs are 5.23, 7.64, and 14.70, respectively. In each simulation run, each sensor node is assumed to have infinite data traffic of $0.01 \times C$ bits per second to send to the CN where the medium capacity C is assumed to be 1 bit per second. Initially, all nodes' batteries are full and have 1 Joule worth of energy ($B_i(t_0) = 1 \ \forall i$). The amount of energy consumed due to the communication of one bit ϵ_{ij} is assumed to be $10^{-8} \times d^2$ for any pair (i, j) of neighbor nodes. Note that, once the transmission range d is chosen, the amount of energy per transmitted bit is the same for all nodes and does not depend on the distance between the sender node and its receiving neighbor.

Each simulation consists of (i) solving the scheme—i.e., determining the routes to the CN, (ii) routing the network traffic using the obtained solution for T seconds, and (iii) updating the battery levels and the lifetimes of all active nodes. These three steps are repeated until every sensor node is either depleted of its energy resources or disconnected from the coordinator node. For each of the three studied average node degrees, the measured lifetime is averaged over all the simulated feasible graphs. Unlike in Subsection 5.1, here the proposed routing scheme considers the MAC contention constraints.

Let *average maximal lifetime* be the average over all nodes of the amount of time that runs out each node's full battery provided that each node adjusts its transmit power so that it communicates directly with the CN without relying on other nodes to forward its traffic. We define the *normalized lifetime* of a node as the ratio of its absolute lifetime achieved under a given routing scheme to the average maximal lifetime. We also define the *computational frequency*, F, as the average maximal lifetime over the optimization horizon T. The parameter F represents the number of T-periods the CN computes and forwards the routes until approximately half of the nodes die.

5.2.2 Result Analysis

Figs. 4-6 show the normalized lifetime as a function of the percentage of dying nodes respectively for d equals 35, 25 and 21. (A bar in a figure corresponding to an x-axis value of $x\%$ and a y-axis value of $y\%$ can be interpreted as $x\%$ of the nodes live only for $y\%$ of their maximal lifetime.) Fig. 4 illustrates the normalized lifetime of the nodes averaged over 62 feasible graphs whose δ is 14.70 with a computational frequency F equal to 100. The figure shows that when the Proposed routing scheme is used, the first 10% dying nodes live for approximately 78% of their maximal lifetimes. However, 10% of the nodes live only for approximately 59, 58, 55, and 32% of their maximal lifetimes when the Redirect flow, Conditional max-min, Max-min, and Min-total energy schemes are used, respectively. Note that even up to the first 50% dying nodes, the Proposed scheme provides a longer lifetime than all of the other four schemes. Since the Proposed approach finds routes that optimize energy consumption with respect to all the nodes as opposed to only a set of nodes, our scheme results in longer lifetimes for the first dying nodes. The Min-total energy scheme, on the other hand, provides the shortest lifetime for the first 50% dying nodes among all the studied schemes because it always chooses the paths with the least

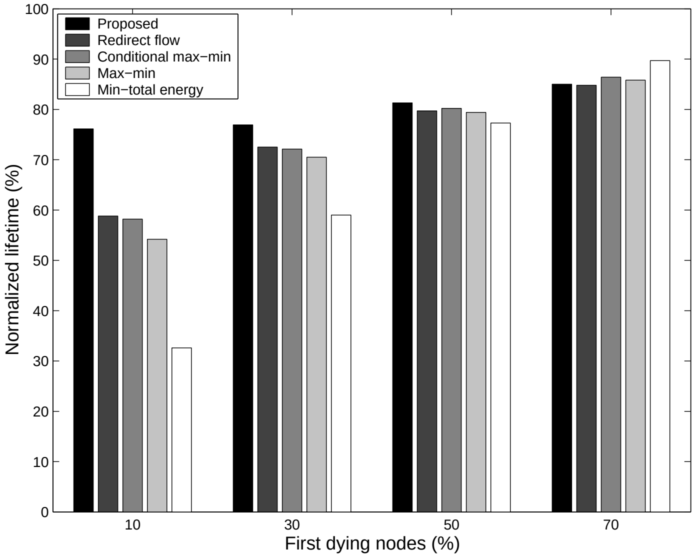

Figure 4: Network lifetime for $d = 35$ and $F = 100$—Averaged over the 62 feasible graphs whose $\delta = 14.70$.

number of hops. This results in the shortest lifetime of the first dying nodes since nodes that happen to be in the shortest path are always chosen independently of their available energy. However, since the **Min-total energy** approach minimizes the total consumed amount of energy, the last dying nodes of the network tend to live for a longer time than those under the other schemes, as evidenced in Fig. 4. In fact, note that under the **Min-total energy** scheme, the last 50% dying nodes live longer than those that live under any of the other four schemes. The other three schemes, **Max-min**, **Redirect flow**, and **Conditional max-min**, yield lifetimes between the **Proposed** and the **Min-total energy** schemes. They all find routes that somehow maximize the lifetime of the network, which explains why they do better than the **Min-total energy** scheme. However, their optimization is not global, which explains why they do worse than the proposed scheme.

In brief, the proposed routing technique tends to maintain the life of as many nodes as possible, which increases the operational time of the network, in detriment of decreasing the lifetimes of the last dying nodes—i.e., all nodes tend to die simultaneously. Conversely, the other schemes achieve shorter lifetimes for nodes that die first while achieving longer lifetimes for those that die last. We believe that

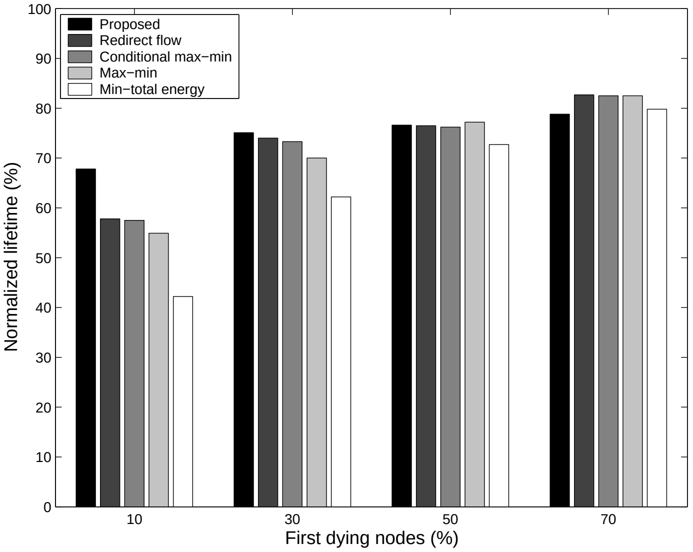

Figure 5: Network lifetime for $d = 25$ and $F = 100$—Averaged over the 52 feasible graphs whose $\delta = 7.64$.

the lifetimes of the first dying nodes (e.g., 10 to 30%) are more important and crucial to the network mission than those of the last dying nodes since loosing a large number of nodes result in less likely useful network.

Effect of δ on the Lifetime: To study the effect of the average node degree on the network lifetime, we also collect the normalized lifetimes of the nodes for $\delta = 7.64$, and $\delta = 5.23$ as shown in Figs. 5 and 6. Only the feasible graphs are simulated—i.e., the 52 graphs for $\delta = 7.64$, and the 16 graphs for $\delta = 5.23$. The computational frequency again equals 100.

Note that the smaller the average node degree, the narrower the gap between the lifetimes achieved by the different schemes (see Figs. 4, 5, and 6). Fig. 6 ($\delta = 5.23$) shows that up to the first 50% of dying nodes, all routing schemes result in almost the same lifetime, except for the Min-total energy scheme. The gap, however, gets wider as the δ gets larger. This is simply because when the average node degree is small—i.e., nodes have few neighbors—the likelihood that nodes have very few (e.g., one or two) possible routes is high. In other words, the fewer the average number of neighbors, the fewer the number of possible routes. Therefore, all routing schemes end up selecting almost the same routes.

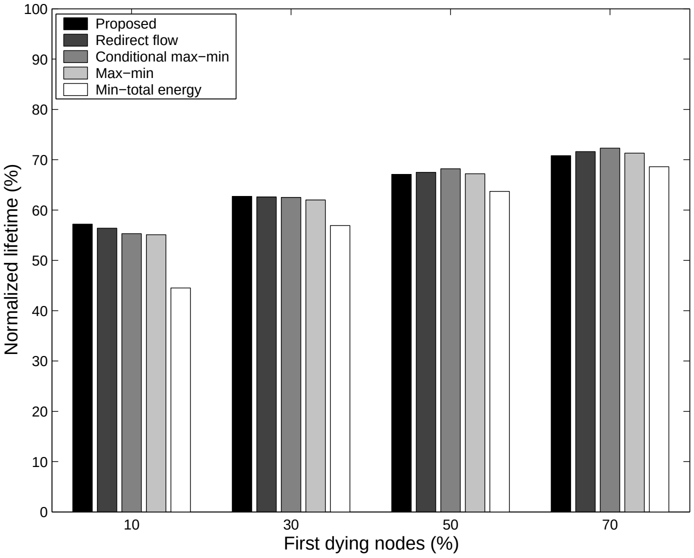

Figure 6: Network lifetime for $d = 21$ and $F = 100$—Averaged over the 16 feasible graphs whose $\delta = 5.23$.

This results in achieving almost the same lifetimes under all the routing schemes. The Min-total energy scheme, however, maintains a relatively large lifetime difference from all the other four schemes. Unlike the other schemes, the Min-total energy scheme chooses the paths that minimize the total consumed energy as opposed to increasing the lifetime, which again explains why the Min-total energy scheme always has the shortest lifetimes for the first dying nodes while the longest lifetimes for the last dying nodes.

Effect of F on the Lifetime: So far in this section, we have used a computational frequency equal to 100, which means that approximately half of the nodes stay alive during 100 optimization horizons. In this subsection, we study and discuss the effect of the computational frequency on the performance of the network. To do so, we simulate the 52 feasible graphs whose δ equals 7.64 for two more frequencies: 200 and 300. For ease of comparison, we only consider the lifetimes of the first 10% dying nodes. The collected results when F equal to 100, 200, and 300 are shown in Fig. 7. Observe that as the frequency increases (i.e., period decreases), the lifetimes achieved under the reported schemes (except the Min-total energy scheme) all tend to increase toward the lifetime achieved under the proposed scheme, which

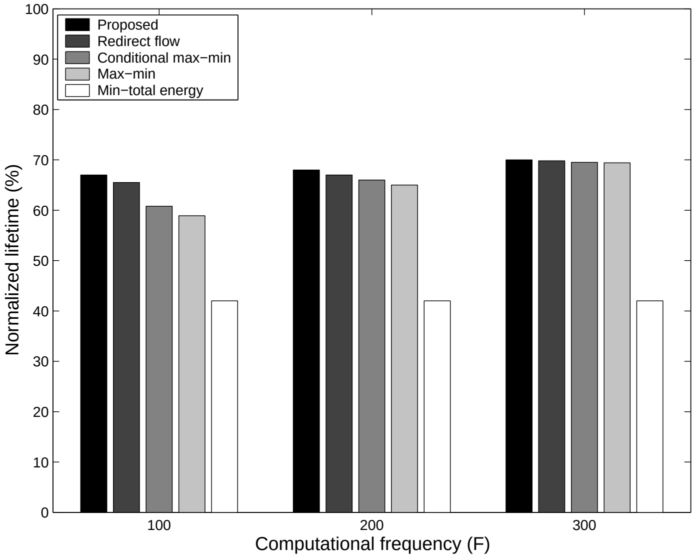

Figure 7: Network lifetime of the first 10% dying nodes for $d = 25$—Averaged over the 52 feasible graphs whose $\delta = 7.64$.

is almost independent of the value of T. As mentioned earlier, one major feature of the proposed scheme is that it optimizes the lifetime in a global manner—it determines a node's route by taking into account the routes of all other nodes. In contrast, Max-min, Redirect flow, and Conditional max-min schemes do not consider the number of paths of which a particular node is already part. In other words, a particular node whose energy level is relatively high may be selected for a path regardless of the total number of routes of which it is part. Therefore, if the period T during which nodes route their traffic is large, then these high energy-level nodes will be exhausted rapidly under any of the reported routing schemes, thereby resulting in shorter lifetimes. This explains the relatively large difference between the achieved lifetimes under the different schemes when $F = 100$. However, if T is small (e.g., $F = 300$), then the nodes with high energy-levels will not be depleted of their energy rapidly. First, since T is small, these nodes will not lose a substantial amount of their energy during a given horizon T. Second, since these nodes have their energy levels lowered, they are less likely to be selected again when the paths are recomputed for the next horizon T. Consequently, nodes tend to live for a longer time under smaller optimization horizons. Note that the lifetimes achieved by the Min-total energy scheme do not depend on how often the routes are recomputed. Again, this is because the shortest paths remain the same independently of the period length.

In studying the effect of the optimization horizon, we notice that one can increase the lifetimes achieved under the reported schemes by using small values of T, and therefore may achieve similar performance to that of the Proposed scheme. However, this typically results in greater computation and higher control message overhead which in turn results in more energy consumption. Therefore, when taking both the energy consumption and the lifetime into consideration, the proposed scheme performs better.

6 Extension to the Active-Idle-Sleep Mode

The packet forwarding scheme described in Subsection 4.3 makes the proposed scheme suitable and more practical for networks where nodes must transition between Active, Idle, and Sleep modes to save energy. It is shown [15, 23] that Idle nodes (nodes which neither transmit nor receive) consume a significant amount of energy; in fact, the amount of consumed energy is almost as high as that consumed by nodes in Receive (Active) mode. As a result, to conserve energy, it is important to put nodes in Sleep mode rather than in Idle mode whenever they are neither transmitting nor receiving. Therefore, power aware routing schemes should be suitable and efficient for such Active-Idle-Sleep networks. If nodes are allowed to sleep as in these networks, then the reported routing schemes require a coordination mechanism by which they are able to discriminate between nodes that are in Sleep mode and those that are not. Such mechanism adds complexity and restriction to the routing algorithm. For example, if a node of a given path transitions to Sleep mode, most of the reported routing approaches (e.g., [12]) need to rerun their algorithms to find new paths. Our approach does not require such extra re-computation, and is not concerned with the extra complexity added by the sleep-awareness mechanism. To satisfy the rate solution, nodes often need to forward their traffic to more than one neighbor with different packet forwarding probabilities. Therefore, nodes can manage locally to send more data (higher rate) to one neighbor while the other neighbor is sleeping. When the sleeping node transitions back to Active mode, then the sending node can transmit at higher rate to that recently awakened node. This is managed so that the overall average rates are equal to the optimal rates. Hence, the proposed scheme requires only local coordination between nodes and their direct neighbors. Note that, as we show in Proposition 1, the proposed energy aware routing solution is cycle-free. This guarantees that all traffic eventually will reach the access point without looping. Our proposed solution does not require any cooperation between the sleep-aware mechanism and the routing algorithm. In addition, there is no need to recompute the routing solution (e.g., paths) when one or more nodes transition to Sleep mode. Therefore, the proposed routing scheme is more suitable and easier to implement in networks where the Active-Idle-Sleep mode is required.

7 Conclusion

In this paper, we propose an energy-efficient and MAC-aware routing scheme for data aggregation in sensor networks that accounts for MAC contention constraints, and systematically deals with both objectives of maximizing the network lifetime and minimizing the total consumed energy. We demonstrate the importance of coupling between the medium access and network layer solutions by studying the effect of not including the medium access constraints on the physical feasibility of the routing solutions. Through simulations, we show that the proposed scheme is more likely to result in feasible solutions for networks that are infeasible under the reported schemes. Further, we infer that rate solutions obtained under the proposed routing scheme are always feasible whereas those obtained under any of the reported schemes may not be feasible.

In addition, we show that the proposed scheme achieves longer network lifetime than those of the reported schemes. The reported schemes achieve shorter lifetimes for the first dying nodes while achieving longer lifetimes for those that die last. However, since the network becomes less useful after loosing a large number of its nodes, it is more important to optimize the lifetimes of the first dying nodes than the last dying ones. Because the proposed scheme achieves longer lifetimes for the first dying nodes in detriment of decreasing the lifetimes of the last dying ones, it yields viable and more practical networks when used.

ACKNOWLEDGMENT

The work reported here was supported in part by U. S. Army Research grant DAAD19-01-1-0504 under a subrecipient agreement S01-24 from the Pennsylvania State University. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the author(s) and do not necessarily reflect the views of the U.S. Army Research Office.

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