Achieving Max-Min Lifetime and Fairness with Rate Allocation for Data Aggregation in Sensor Networks☆

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Abstract

We consider the rate allocation problem for data aggregation in wireless sensor networks with two objectives: 1) maximizing the minimum (Max-Min) lifetime of an aggregation cluster and 2) achieving fairness among all data sources. The two objectives are generally correlated with each other and usually, they cannot be maximized simultaneously. We adopt a lexicographic method to solve this multi-objective programming problem. First, we recursively induce the Max-Min lifetime for the aggregation cluster. Under the given Max-Min lifetime, we then formulate the problem of maximizing fairness as a convex optimization problem, and derive the optimal rate allocation strategy by iterations. We also present low-complexity algorithms that an aggregation cluster can use to determine the Max-Min network lifetime and the fair rate allocation. Our simulation results validate our analytical results and illustrate the effectiveness of the approach.

Keywords: Rate Allocation, Data Aggregation, Lexicographic method, Wireless Sensor Networks

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1. Introduction

Wireless sensor networks (WSNs) have recently received increased attention for a broad array of applications such as surveillance, environment monitoring, medical diagnostics, and industrial control. *Data aggregation* [1, 2] is a fundamental operation in sensor networks in which data packets generated at sensor nodes are to be aggregated in local cluster heads or at a sink node. For example, in target tracking applications [3], some nodes in the network generate physical measurements of an intruding target after sensing its presence. The nodes may then send sensed data via either one hop or multi-hops towards the cluster head or the sink node.

The nature of data aggregation usually results in a tiered structure in sensor networks. Early sensor network designs assume a flat network in which sensors directly transmit their packets to the sink node. More recently, tiered sensor networks [4] have been proposed for use in high data-rate applications (e.g., acoustic [5], imaging [6]). In tiered networks, the lower-tier consists of tiny wireless sensors that transmit data to the closest upper-tier node (usually an embedded 32-bit system with an 802.1x radio). In such networks, when an event is sensed, a relatively large number of nodes might wish to transmit significant volumes of data (either raw samples, or processed information) along one or more trees towards base stations. Rate allocation plays an important role in such situations.

Generally, one basic requirement on rate allocation in wireless sensor networks is to achieve energy efficiency [7], because most sensor nodes are battery-powered and it is practically infeasible to recharge them. The limited size of sensor nodes only allows for very limited energy storage in most applications such as tracking. Although substantial improvements have been achieved in chip design for energy conservation, energy-efficient battery designs still lag behind. Thus, one of the fundamental challenges in sensor networks is their energy efficient operation, and significant research efforts are focusing on this problem. By controlling the data rates, the network lifetime can be maximized [8, 9] if we balance the energy consumption over all nodes in the network. For example, nodes with high remaining energy can be allowed to transmit more data, while those with low energy should transmit less. Without such balanced energy consumption, some nodes may quickly exhaust their power, causing network partitions or malfunctions.

Another requirement for many data aggregation applications is to achieve fairness among source rates [10, 11]. Typically, applications can achieve better performance when data gathered from different source nodes are identical in terms of data rate. For instance, equal amount of data from some video sensor nodes can help the cluster head build a whole-scene image or video. To achieve fairness, it is important to have data rates among all source nodes as equal as possible. This requirement can be met only if we are able to obtain a fair amount of data from each of the sensors that are part of the network. This leads to the fair rate allocation amongst all sources in the network. Hence, rate allocation amongst sources need not only be efficient (i.e., maximize network lifetime), but must also ensure fairness [12, 11, 13].

In this paper, we present the design of a distributed mechanism for fair and energy-efficient rate allocation strategy in wireless sensor networks. In general, the design of such a mechanism is complicated by the radio characteristics of shared wireless channels (i.e., IEEE 802.15.4). As such, the channel arbitration used by the MAC layer and the quality of paths determined by the routing protocol can also impact the quality of any solution for the rate allocation problem. For simplicity, we build our work upon the de facto standard MAC layer (i.e.,CSMA) and routing layer (i.e., MintRoute [14]). We defer to future work the examination of an optimal cross-layer design which jointly designs the MAC layer, the routing layer, and a rate allocation scheme.

In most cases, an optimized rate allocation that simultaneously maximizes the network lifetime and fairness is difficult as the two objectives are correlated with each other. For maximizing the network lifetime, it is better to bias the rate allocation for nodes with different remaining energy/transmission cost, as this will balance the energy consumption. However, for maximizing fairness, it is better to average the data rate of all nodes as much as possible. There is an inherent trade-off between biased rate allocation (lifetime maximization) and even allocation (fairness) [15, 16]. Furthermore, the problem becomes more difficult for arbitrary communication patterns [17]. As we show in this paper, we can leverage the tree-based traffic pattern prevalent in wireless sensor networks to obtain a distributed and fair rate allocation mechanism. Specifically, we make the following contributions.

Our Contribution: We formulate the above problem as a multi-objective programming problem and adopt a lexicographic method [18] to solve the problem. First, we recursively maximize the minimum (Max-Min) network lifetime in a local aggregation tree. Under the given maximum lifetime, we then formulate the problem of maximizing fairness as a convex optimization problem, and derive the optimal rate allocation strategy, considering the impact of interferences. We also present a low-complexity algorithm to compute the Max-Min network lifetime and the optimal rate allocation for fairness. Our simulation studies illustrate the effectiveness of our algorithm in finding an optimal rate allocation strategy. To the best of our knowledge, this is the first result on rate allocation in sensor networks that simultaneously maximizes network lifetime and fairness for data aggregation using a lexicographic method.

The rest of the paper is organized as follows: In Section 2, we overview the related work on rate allocation for sensor networks. In Section 3, we describe the network topology, transmission power model, and the notations that we use in the paper. In Section 4, we consider the scenario of multi-frequency with full-duplex for a node, and mathematically analyze the problem model and present our lexicographic solution. We extend the same problem to the scenario of multi-frequency with half-duplex in Section 5 and derive new solutions. We report our simlation-based experimental results in Section 7, and conclude in Section 8.

2. Related Work

The problem of rate allocation and energy management in wireless sensor networks have been extensively studied. For example, to maximize the network lifetime, Bhardwaj *et. al.* present an upper bound on the network lifetime for energy-efficient collaborative data gathering with optimal role assignments for different nodes [19]. In [20], Sankar *et. al.* present a distributed algorithm at the network layer to maximize the network lifetime. This algorithm can guarantee bounded approximation error for flow routing.

Regarding the impact of rate allocation on the network lifetime, most works study how to maximize the minimum (Max-Min) network lifetime for different allocation strategies. For example, Xue *et. al.* [8] present a dual decomposition method and an approximation algorithm to determine the optimal network lifetime for data aggregation, where each node has multiple routing paths to the sink node. In [21], Hou *et. al.* study the Max-Min rate allocation among all nodes with a system lifetime requirement. They use a linear programming approach to solve the Max-Min lifetime problem and develop a polynomial-time algorithm.

The problem of achieving fairness in rate allocation has also been well studied. For instance, in [22], the authors study how to achieve MAC-layer fairness among one-hop flows within a neighborhood. In [7], the fair data collection problem is studied within the network utility maximization (NUM) [23] framework. In [24], Chen *et al.* determine the maximum rate at which individual sensors can produce data without causing congestion in the network and unfairness among peer nodes.

Past works have also explored the trade-off between the Max-Min network lifetime and fair rate allocation. In [16], Nama *et. al.* present a general cross-layer framework that takes into account radio resource allocation, routing, and rate allocation for achieving trade-offs between lifetime maximization and fairness. The authors solve the tradeoff problem via a dual decomposition method. In [15], a similar problem is addressed at the transport layer. The idea in this work is to construct a new optimization function by linearly adding up the two objective functions (i.e., lifetime and the objective function representing fairness) and deriving an optimal solution for maximizing the newly constructed function.

The differences between our work and [16, 15] include the following. First, we study the tradeoff problem in a cluster which has a tree-like network topology that is more suitable for data aggregation. Second, we adopt a lexicographic method in which we favor network lifetime maximization over fairness (no such preferences exist in previous works). We do so, because network lifetime is strongly correlated to energy consumption, which is the most performance-critical aspect of sensor networks.

3. Network Topology and Preliminaries

3.1. Network Topology

We consider a static and symmetric multi-hop wireless sensor network $G = (V, E)$, where $V = \{0, 1, 2, \cdots, N\}$ is the set of sensor nodes and E is the set of undirected edges. In this graph-theoretical model of wireless sensor networks, we use the terms nodes and vertices interchangeably.

We assume that the network topology for data aggregation is a tree structure (i.e., an aggregation tree) which is widely adopted by previous works [25, 26]. There are three types of sensor nodes in the network: source nodes, relay nodes, and the sink node (or local cluster head). The *source nodes* are *leaf nodes* which generate sensor data. The function of a source node is simple: once triggered by an event, it starts to capture live information about the target, which is then directly sent to the local cluster head within one hop or multiple hops. Only source nodes can generate data in our system. A *relay node* does not generate data. Its functions include: 1) receiving data from its children nodes which can be relay nodes or source nodes, and 2) forwarding the received data to the next hop toward the cluster head (i.e., the root node). The *cluster head*/sink node is the aggregation end point.

We assume high data rates (e.g., raw acoustic or image data sampling) generated by a relatively large number of nodes. This data can traverse multiple hops before reaching the sink node or a local cluster head for data aggregation.

There are two scenarios of radio technology in our application scenario: (1) Multi-frequency with Full-duplex (or multiple transceivers). In this case, the radio interference is avoided by multiple frequencies and a node can transmit and receive data simultaneously due to multiple transceivers or full duplex; (2) Multi-frequency with Half-Duplex (or single transceiver). In this case, although interference is avoided, a node cannot transmit and receive data simultaneously.

We do not assume any specific routing protocol. A single-path routing protocol (e.g., MintRoute [14]) can work underneath our proposed rate allocation algorithms. We also assume reliable end-to-end data transmission by using any existing reliable mechanism [27, 28].

Besides, we make additional assumptions as follows: (1) All sensor nodes and the cluster head are time-synchronized; (2) Any sensor node has at most one parent in the aggregation tree; (3) Each sensor node can measure its transmission energy per byte and the remaining battery capacity; and (4) Within each cluster, the source nodes can sense events (i.e., targets) and can transmit the sensed data to the relay node simultaneously.

In the rest of the paper, for convenience, we will use the terms leaf node and source node interchangeably, and the terms root node and cluster head interchangeably.

3.2. Power Dissipation Model

A detailed power consumption model for each component in a wireless sensor node can be found in [29]. The power consumption due to data communication (i.e., receiving and transmitting) is the dominant factor of a sensor node's overall power consumption. Suppose there are N sensor nodes in a cluster. Each node is denoted as $n_i (i \leq N)$. We denote g_i as the bit rate from node n_i to its next hop node, and c_i as the transmission power cost over the radio link. We denote,

$$w_i = \alpha + \beta \cdot d_i^m$$

where α is a distance-independent constant term, β is a coefficient term associated with the distance-dependent term, d_i is the distance between the sensor node n_i and its next-hop node, and m is the path-loss index, with $2 \leq m \leq 4$. Typical values for these parameters are $\alpha = 50nJ/b$ and $\beta = 0.0013pJ/b$ (for m=4) [29]. The power dissipation at the transmitter, mostly being source nodes, can be modeled as:

$$p_s(i) = w_i \cdot g_i. \tag{1}$$

The power dissipation at a receiver, mostly being relay nodes or the sink node, or the cluster head for receiving data, can be modeled as:

$$p_r(i) = \rho_i \cdot g_i \tag{2}$$

where the typical value for the parameter ρ is $50nJ/b$ [29].

For a relay node, the power dissipation consists of two parts: receiving power and transmitting power. The power dissipation for a relay node can be modeled as:

$$p_t(i) = (w_i + \rho_i) \cdot \ g_i. \tag{3}$$

For convenience in presentation, we adopt an uniform denotation:

$$p_{s_k}(i) = c_{s_k} \cdot \ g_{s_k} \tag{4}$$

for the power dissipation in sensor node n_{s_k}. If the node is a source node, $c_{s_k} = w_{s_k}$. For a receiving node, $c_{s_k} = \rho_{s_k}$; for a relay node, $c_{s_k} = w_{s_k} + \rho_{s_k}$.

In our power consumption model, we omit the feed-back messages since we assume multimedia applications over WSNs, like image reconstruction and the feedback data (i.e. , acknowledgement message) rate is relatively small comparing to the multimedia data rate from sensor nodes to the sink node.

3.3. Notations

A sensor node is denoted as $n_i(i = 0, \cdots, N)$ and the sink node as n_0. The set of all source nodes is denoted as $\mathcal{S}_0 = \{s_k | n_{s_k} \in \mathcal{N}\}$ in which s_k is the index in $[0, N]$. In addition, we define the set of source nodes rooted at node n_i as $\mathcal{S}_i$, and $\mathcal{S}_i = \{n_i\}$ if n_i is a source node.

Outgoing rate from source node/relay node is defined as g_{s_k} for node n_{s_k}. We also define an unified term c_{s_k}, which represents the energy requested for transceiving one unit of data. Based on Equations 1, 2, and 3, for a source node, $c_{s_k} = w_{s_k}$; for a relay node, $c_{s_k} = w_{s_k} + \rho_{s_k}$; and for the cluster head $c_0 = \rho_0$.

The minimum system lifetime, denoted as T_{min}, is defined as the operational time of the local cluster until the first node in the cluster runs out of power. We denote the initial remaining energy of a node n_{s_k} as E_{s_k}. The transmission capacity over a radio channel is denoted as R.

For convenience, we summarize all notations in Table 3.3.

3.4. Bit Capacity

For convenience in presentation, we introduce the notion of "Bit Capacity," which is defined as the largest amount of data that can be transmitted through one node before dissipating all of its remaining energy.

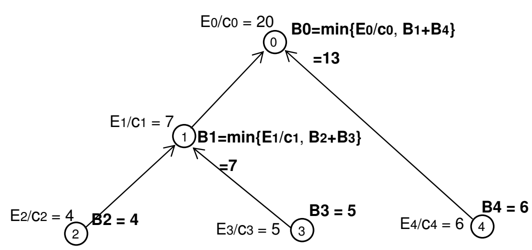

Figure 1: Aggregation Topology and Bit Capacity

Formally, it is defined as follows:

Definition 1. *Let B_i be the* Bit Capacity *of node n_i, which is defined as:*

$$B_i = \begin{cases} min\{\frac{E_i}{c_i}, \sum_{d_k \in D_i} B_{d_k}\}, & n_i \ is \ relay \ node \\ E_i/c_i, & n_i \ is \ leaf \ node \end{cases} \quad (5)$$

Table 1: Notations

Notation	Description
$n_i(i = 0, \cdots, N)$	Sensor node. The sink node is defined as n_0
$\mathcal{S}_0 = \{s_k \| n_{s_k} \in V\}$	Set of source nodes which generate sensor data; s_k is the index of the source node n_{s_k} among V
$\mathcal{S}_i$	Set of source nodes rooted at node n_i. If n_i is a source node, $\mathcal{S}_i = \{n_i\}$
g_{s_k}	Outgoing rate from sensor node n_{s_k}. For a leaf node, it is the source data rate generated by source sensor nodes
c_{s_k}	Power dissipation for sensor node n_{s_k}. For a source node, $c_{s_k} = w_{s_k}$; for a receiving node $c_{s_k} = \rho_{s_k}$; for a relay node, $c_{s_k} = w_{s_k} + \rho_{s_k}$
E_{s_k}	Initial remaining energy of node n_{s_k}
T_{min}	Network lifetime, defined as the operational time of the cluster until the first node runs out of power
R	Radio channel capacity

where D_i is the direct children set of node n_i, and d_k is the index number in $[1, N]$.

For example, in Figure 1, for all nodes at the initial state, $B_0 = 20$, $B_1 = 7$, $B_2 = 4$, $B_3 = 5$, and $B_4 = 6$. After the first iteration, $B_1 = min\{E_1/c_1, B_2 + B_3\} = 7$ and $B_0 = min\{E_0/c_0, B_1 + B_4\} = 13$. Thus, the Bit Capacity of the cluster head is 13.

4. Multi-Frequency with Full-Duplex

We first consider a node with multi-frequency channel and full duplex (or multi-transceiver), in which a node can transmit and receive data simultaneously.

4.1. Problem Definition

Energy consumption constraints: For each sensor node n_i in V, the energy consumption for transmitting or receiving within the network lifetime (T_{min}) must not exceed its initial remaining energy. This means,

$$\forall i \in [1, N],\ T_{min} \cdot c_i \cdot \sum_{s_k \in \mathcal{S}_i} g_{s_k} \leq E_i. \tag{6}$$

where $\sum_{s_k \in \mathcal{S}_i} g_{s_k}$ represents the data rate accumulated by all leaf nodes rooted at n_i. For the sink node/cluster head, which is the root node of the aggregation tree, the constraint is:

$$T_{min} \cdot c_0 \cdot R \leq E_0. \tag{7}$$

Capacity constraints: To obtain the best performance, the accumulated rates from all leaf nodes must not exceed the channel capacity, no matter whether the nodes include the sink node or relay nodes. Thus, we have:

$$\forall s_k,\ \sum_{s_k \in S_0} g_{s_k} = R. \tag{8}$$

Furthermore, all the rate flows must be nonnegative, and the union of all children sets consists of the children set of the sink node/cluster head. That is:

$$\forall i \in [1, N], S_0 = S_1 \bigcup S_2 ... \bigcup S_N, \&,\ g_i > 0. \tag{9}$$

Problem Formulation: The fairness among data rates of all source nodes is defined as the product of all source rates. When we maximize the product, it is equivalent to maximizing the *geometric mean* so that we can achieve fairness. Thus, we formulate the rate allocation problem with the objective of maximizing both the minimum (Max-Min) network lifetime T_{min} and the product of source rates (fairness) as follows:

$$\begin{aligned} P1: \quad maximize: \quad & T_{min} \\ & \textstyle\prod_{s_k \in S_0} g_{s_k} \\ subject\ to: \quad & Inequalities\ 6,\ 7,\ 8,\ 9 \end{aligned} \tag{10}$$

This is a non-linear multi-criteria programming problem. We solve the problem via a lexicographic method [18]. By this method, we first maximize one objective, T_{min}, and obtain the solution space of rate vectors $\overline{g}$ for all source nodes. Within this solution space, we then derive a rate vector $\overline{g}$ to maximize $\prod_{s_k \in S_0} g_{s_k}$, and thereby seek to ensure fairness under the given Max-Min network lifetime (denoted as T_{mm}).

There are two reasons to select T_{min} as the dominant objective. First, the Max-Min network lifetime is strongly correlated to energy consumption, which is one of the most performance-critical aspect of sensor networks. Secondly, if we maximize $\prod_{s_k \in S_0} g_k$ first, the only optimal solution will be determined due to the convex feature of the objective function, which will make the lexicographic method ineffective.

4.2. Max-Min Lifetime

Theorem 1. *Suppose the* Bit Capacity *of the root node (n_0) is B_0. Then the Max-Min network lifetime T_{mm} is:*

$$T_{mm} = \frac{B_0}{R} \tag{11}$$

Proof. The proof is by induction. Suppose an aggregation tree has H layers.

Base case: When $H = 1$, Equation 20 is obviously true.

Inductive Hypothesis: Assume that Equation 20 holds when the aggregation tree has $m(> 1)$ layers. We now show that Equation 20 also holds when the tree has $m + 1$ layers.

Inductive Step: For $H = m+1$, let the children set of root node n_0 is D_0. Then, for each node $d_k \in D_0$, the subtree rooted at n_{d_k} has at most m layers, and its Max-Min lifetime is given by $T_{min} = \frac{B_{d_k}}{R_{d_k}}$, where R_{d_k} is the outgoing data rate from node n_{d_k}.

Thus, $\forall d_k \in D_0$, $T_{min} \cdot R_{d_k} \leq B_{d_k}$. Therefore, we have $T_{min} \leq \frac{\sum_{d_k \in D_0} B_{d_k}}{\sum_{d_k \in D_0} R_{d_k}} = \frac{\sum_{d_k \in D_0} B_{d_k}}{R}$. Also, for the root node n_0, its energy constraint is given by Equation 6, or expressed as $T_{min} \cdot R \leq \frac{E_0}{c_0}$. Therefore, we can show that $\max\{T_{min}\} = \frac{1}{R} \cdot \min\{\frac{E_0}{c_0}, \sum_{d_k \in D_0} B_{d_k}\}$, or $T_{mm} = \frac{B_0}{R}$.

It is shown in Theorem 1 that the maximum lifetime only depends on the Bit Capacity of the root node and the channel capacity.

4.3. Fairness of Rate Allocation

Once we have obtained the Max-Min network lifetime for the aggregation tree, the remaining objective is to maximize the product (or geometric mean) of all the rates. This problem can be formulated as:

$$\begin{array}{lll} P: & \textit{maximize}: & \prod_{s_k \in S_0} g_{s_k} \\ & \textit{subject to}: & \forall s_k \in \mathcal{S}_0,\ T_{mm} \cdot \sum\limits_{s_k \in \mathcal{S}_i} g_{s_k} \leq B_i \\ & & T_{mm} \cdot \sum\limits_{s_k \in \mathcal{S}_0} g_{s_k} \leq B_0 \\ & & \forall s_k \in [1, N],\ g_{s_k} > 0 \end{array} \tag{12}$$

We can express the constraints as $A \cdot \overline{g} \leq C$, where A is a matrix with $(K+1) \times |S_0|$ dimensions and C is a vector with $K+1$ items. This is a typical convex optimization problem with linear constraints, and it can be solved by optimization methods such as Dual Decomposition [30].

However, by analyzing the problem's constraint structure, we adopt a low-complexity solution. Our approach is to iteratively reduce the number of constraints under the convex objective function. To understand how to address the optimization problem, we first consider the simple case in which the tree has only 2 layers.

Proposition 1. *Suppose the aggregation tree has only two layers, and its K children are sorted as $B_1 \leq B_2 \leq ... \leq B_K$. Under the maximized cluster lifetime T_{mm}, the optimal rate allocation for all leaf nodes is given by:*

$$g_j = \begin{cases} \frac{1}{T_{mm}} \cdot \min\{B_j, \frac{B_0}{K}\}, & j = 1 \\ \frac{1}{T_{mm}} \cdot \min\{B_j, \frac{B_0 - T_{mm} \cdot \sum_{k=1}^{j-1} g_k}{K-j+1}\}, & 1 < j \leq K \end{cases} \tag{13}$$

By Lagrange relaxation theory, it is not difficult to prove Proposition 1. In most cases, an aggregation tree has more than two layers. Our objective is to reduce the constraints in Equation 12 equivalently to a constraint structure for a two-layer tree.

Proposition 2. *Equation 12 can be equivalently reduced to the following problem which has the same constraint structure as that in a two-layered aggregation* *tree:*

$$\begin{aligned} maximize: \quad & \prod_{s_k \in \mathcal{S}_0} g_{s_k} \\ subject\ to: \quad & \forall s_k \in \mathcal{S}_0,\ T_{mm} \cdot g_{s_k} \leq B^{'}_{s_k} \\ & T_{mm} \cdot \sum_{s_k \in \mathcal{S}_0} g_{s_k} \leq B_0 \\ & \forall s_k \in [1, N],\ g_{s_k} > 0 \end{aligned} \tag{14}$$

where $B^{'}_{s_k}$ is the Bit Capacity value of node n_{s_k} after constraint reduction.

Proof. The proof is by induction. Suppose the aggregation tree has H layers.

Base case: $H = 2$. We can directly apply Proposition 1 without constraint reduction.

Inductive hypothesis: Suppose that when $H = m$, the proposition holds.

Inductive Step: We need to show that when $H = m + 1$, the proposition holds. Suppose the root node has a children set D_0. For each node $d_k \in D_0$, if n_{d_k} is a relay node, suppose the set of leaf nodes rooted at n_{d_k} is $\mathcal{S}_{d_k}$. For the subtree rooted at n_{d_k} (with $K^{'}$ leaf nodes), since its layer is less than m, based on the inductive hypothesis, the convex optimization problem can be reduced to the following problem:

$$\begin{aligned} P^{''}: \quad maximize \quad & \prod_{s_k \in \mathcal{S}_{d_k}} g_{s_k} \\ subjectto \quad & \sum_{s_k \in \mathcal{S}_{d_k}} g_{s_k} \leq \tfrac{1}{T_m} \cdot B_{d_k} \\ & \forall s_k \in \mathcal{S}_{d_k}, g_{s_k} \leq \tfrac{1}{T_m} \cdot B^{''}_{s_k} \end{aligned} \tag{15}$$

where $B^{''}_{s_k}$ is Bit Capacity value of node n_{s_k} after constraint reduction. Based on Proposition 1, $\forall j \in [1, K^{'}]$, the optimal value of g_j to maximize the fairness in the subtree is:

$$g_j = \begin{cases} \frac{1}{T_m} \cdot min\{B^{''}_j, \frac{B_{d_k}}{K'}\}, & j = 1 \\ \frac{1}{T_m} \cdot min\{B^{''}_j, \frac{B_{d_k} - T_m \cdot \sum_{k=1}^{j-1} g_k}{K' - j + 1}\}, & 1 < j \leq K^{'} \end{cases} \tag{16}$$

Let $B^{'}_{s_k} = g_j * T_m$. Since $\forall s_k \in S_{d_0}, g_{s_k} \leq g_j$, we have $\forall s_k \in S_{d_k}, g_{s_k} \leq \frac{1}{T_m} \cdot B^{'}_{s_k}$.

The other constraint for the root node is: $\sum\limits_{s_k \in \mathcal{S}_0} g_{s_k} \leq \frac{1}{T_{mm}} \cdot B_0$. Thus, the proposition holds.

Once the constraints are equivalently reduced to that in Equation 14, the final rate allocation vector is derived based on Proposition 1.

We denote $B^{'}_{s_k}$ for node n_{s_k} in each iteration as $GB^{'}(s_k)$, which is called the **Geometry Bit Capacity**. We also denote $GB(s_k)$ as the **Geometry Bit Capacity** in the final iteration, which represents the optimal transmitted/received bits for node n_{s_k} in each intermediate iteration, to obtain the global fairness. Then we have,

Proposition 3. *By lexicographic method, to achieve fairness, the rate allocation strategy for all leaf nodes $g_{s_k} \in S_0$ is as follows:*

$$g_j = \frac{GB(s_k)}{T_{mm}} \tag{17}$$

Proof. Suppose the aggregation tree has K leaf descendants. Also, suppose that there are p iterations. In the $(p-1)^{th}$ iteration, the sorted set of Geometry Bit Capacities for all leaf descendants is $\{GB^{(p-1)}(j)\}$, where $GB^{(p-1)}(1)$ $< \cdots < GB^{(p-1)}(K)$.

In the final iteration, $GB(s_k)$ is expressed as:

$$GB(j) = \begin{cases} \min\{GB^{(n-1)}(j), \frac{B_0}{K}\}, & j = 1 \\ \min\{GB^{(n-1)}(j), \frac{B_0 - \sum_{k=1}^{j-1} GB(k)}{K-j+1}\}, & 1 < j \leq K \end{cases}$$

The constraint structure in the final constraint is the same as that in a two-layer aggregation tree. Based on Proposition 2, this Proposition holds.

We now give an intuitive explanation via the following example. In Figure 2, initially, $B_2 = 4$ and $B_3 = 5$. After one iteration, we reduce the layer of the original tree by 1. The leaf node (node 2 and node 3) will get a new Bit Capacity $B^{'}_2 = \frac{1}{2} \cdot 7 = 3.5$, $B^{'}_3 = 3.5$ (based on Proposition 1) and node 4 will keep its current Bit Capacity. After reduction, the new tree has two layers and we can apply Proposition 1 to get the final rates for all leaf nodes as: $r_2 = \frac{1}{T_m} \cdot min\{3.5, \frac{13}{3}\} = \frac{3.5}{T_m}$, $r_3 = \frac{1}{T_m} \cdot min\{3.5, \frac{13-3.5}{2}\} = \frac{3.5}{T_m}$, and $r_3 = \frac{1}{T_m} \cdot min\{6, \frac{13-7}{1}\} = \frac{6}{T_m}$. T_m is calculated as that in Equation 20.

Based on Propositions 1 and 2, we present algorithms to compute the maximum lifetime and the fair rate allocation. The algorithms contain both the distributed part and the centralized part. The intermediate roots of different

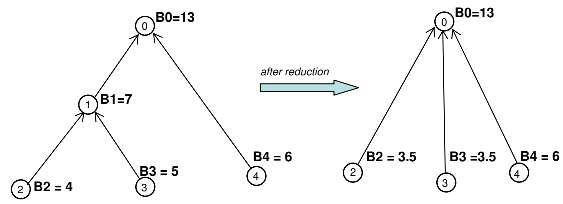

Figure 2: Network Topology

subtrees will distributively calculate the Bit Capacity and the Fair Bit Bound for their leaf children. But the final maximum lifetime and optimal rate vector is calculated by the Cluster Head, in a centralized way.

Algorithm 1 shows the operation for all source nodes.

Algorithm 1: Operations in Leaf Node (Source Node) n_i:

Initialization:
  E_i = getInitialEnergy(n_i);
  c_i = getPowDispPara(n_i);
  $B_i = GB(i) = \frac{E_i}{c_i}$;
  Report $\{B_i, \{GB(i)\}\}$ to its parent node;
  On receiving allocated rate vector $\overline{g} = \{g_{s_k}\}$
  If $s_k = i$, set $g_i = g_{s_k}$.

The operations for the relay nodes and the root node (cluster head) are described in Algorithm 2 and Algorithm 3, respectively. Relay nodes and the root node need to first calculate the Bit Capacity for the leaf children (line 4 of both algorithms). D_i and D_0 (in line 3 of both algorithms) is the children set of n_i. $\mathcal{S}_{d_k}$ is the source node in the subtree rooted at n_{d_k}. Relay nodes must also update the **Geometry Bit Capacity** for all leaf children. This is shown from line 5 to line 10 of Algorithm 2. After obtaining the result of the computation, they report the result to their parent nodes for further iterations. A relay node also informs its children about the allocated rate vector from its parents.

The root node calculates the optimal rate vector after receiving information from all the leaf nodes (i.e., source nodes). The node then multicasts the fair rate allocation to all the leaf nodes (line 13 of Algorithm 3).

Algorithm 2: Operations in Relay Node n_i for full-duplex scenario:

Initialization:
E_i = getInitialEnergy(n_i);
c_i = getPowDispPara(n_i);
$B_i = GB(i) = \frac{E_i}{c_i}$;
On Receiving Reports $\{B_{d_k}, \{GB(s_j)|n_{s_j} \in \mathcal{S}_i\}\}$**:**
$B_i = \min\{B_i, \sum_{s_k \in \mathcal{S}_i} B_{s_k}\}$;
Sort the members in $\{GB(s_j)|n_{s_j} \in \mathcal{S}_i\}$;
$\{GB(j)\}$ = Sorted set in which $GB_{j-1} \leq GB_j$;
$sum = 0$;
for $k = 1$ **to** $|S_i|$ **do**
  $GB(k) = \min\{GB(k), \frac{B_i - sum}{|S_i|}\}$;
  $sum = sum + GB(k)$;
Report $\{B_i, \{GB(s_j)|n_{s_j} \in \mathcal{S}_i\}\}$ to the parent node;
On receiving allocated rate vector $\overline{g}$**:**
Multicast the information to all subtrees;

4.4. Analysis of Algorithms

Theorem 2. *Algorithms 2 and 3 have the time complexity of $\mathcal{O}(NlogN)$, and the message complexity of $\Theta(N)$, where N is the number of nodes in the aggregation tree.*

Proof. The most computationally intensive part is for sorting all elements in $\{GB(s_j)\}$. Since there are at most N elements in $\{GB(s_j)\}$, the time complexity of this part is at least $\mathcal{O}(nlogn)$. The other computationally significant component is for computing the rate for each node over the sorted set $\{GB(s_j)\}$; this time complexity is $\mathcal{O}(N)$ according to Proposition 3. Thus, the total time complexity is $\mathcal{O}(NlogN)$.

As for the message complexity, each node should send a message to its parent to update information. The least number of messages is equal to the number of edges in the aggregation tree (i.e., N edges). Thus, the total message complexity is $\Theta(N)$.

Suppose the average one-hop round trip delay is RTT. Now, the lower bound of the delay overhead is $N \cdot RTT$ for a leaf node receiving the allocated rate.

Algorithm 3: Operations in Root Node (Cluster Head) n_0 for full-duplex scenario

Initialization:
  E_0 = getInitialEnergy(n_0);
  c_0 = getPowDispPara(n_0);
  $B_i = GB(0) = \frac{E_0}{c_0}$;
On Receiving Reports $\{B_{d_k}, \{GB(s_j)|n_{s_j} \in \mathcal{S}_0\}\}$**:**
  $B_0 = \min\{B_0, \sum_{s_k \in \mathcal{S}} B_{s_k}\}$;
  $T_{mm} = \frac{B_0}{R}$;
  Sort the members in $\{\{GB(s_j)|n_{s_j} \in \mathcal{S}_0\}$;
  $\{GB(j)\}$ = Sorted set in which $GB_{j-1} \le GB_j$;
  $sum = 0$;
  for $k = 1$ **to** $|\mathcal{S}_0|$ **do**
    $g_k = \frac{1}{T_{mm}} \cdot \min\{GB(k), \frac{B_0 - sum}{|\mathcal{S}_0| - k + 1}\}$;
    $sum = sum + GB(k)$;
  $\overline{g} = \{g_{s_k}|s_k \in \mathcal{S}_0\}$;
  Multicast $\overline{g}$ to its children;

5. Multi-Frequency with Half-Duplex

Now we consider the scenario where each sensor node has multi-frequency channel with half-duplex transmission mode (i.e., single transceiver). The *half-duplex* mode is more practical for most radios in wireless sensor networks (i.e., IEEE 802.15.4).

5.1. Problem Definition

For the half-duplex transmitting mode, a node usually cannot transmit and receive data simultaneously. Thus, the incoming rates cannot exceed $R/2$ for a relay node.

$$\forall s_k, \sum_{s_k \in S_i} g_{s_k} \le \frac{R}{2}, \ n_i \ is\ a\ relay\ node. \tag{18}$$

Except for this constraint, the energy consumption constraints and the capacity constraint for the root node are exactly the same as the inequalities given in Equations 6, 7, 8, and 9 in Section 4.1. Thus, the problem can be formulated as:

$$\begin{aligned} P2: \quad maximize: \quad & T_{min} \\ & \textstyle\prod_{s_k \in S_0} g_{s_k} \\ subject\ to: \quad & Inequalities\ 6,\ 7,\ 8,\ 9\ and\ 18 \end{aligned} \tag{19}$$

The difference between the problem $P2$ and $P1$ is that $P2$ has an additional constraint (i.e., the inequality of Equation 18), which is caused by the half-duplex transmission mode. Similar to the first scenario, we can solve the problem by a lexicographic method [18], which is a typical approach for solving multi-criteria programming problems. By this method, we first maximize the minimum network lifetime T_{min}, and then derive a rate vector $\overline{g}$ to maximize $\prod_{s_k \in S_0} g_{s_k}$ under the given Max-Min lifetime. The rationale for adopting such a lexicographic solution is similar to that given in Section 4.1.

5.2. Max-Min Lifetime

Suppose that the sink node (n_0) has l direct children, each denoted as $n_{0,i}(1 \leq i \leq l)$.

Theorem 3. *Suppose the* Bit Capacity *of the root node n_0 is B_0 and the* Bit Capacity *of each child $n_{0,i}$ of n_0 is $B_{0,i}$. Among all Bit Capacities of the direct children which are relay nodes, let B_m denote the maximum Bit Capacity. Then the maximum minimum (Max-Min) network lifetime T_{mm} is given by:*

$$T_{mm} = \frac{B_0}{\min\{R, \frac{R}{2}\frac{\Sigma_{1 \leq i \leq l} B_{0,i}}{B_m}\}} \tag{20}$$

Proof. The rates for all children $n_{0,i}(1 \leq i \leq l)$ of the sink node should satisfy: $T_{min} \cdot g_{0,i} \leq B_{0,i}$. Adding them up, we have,

$$T_{min} \cdot \sum_{1 \leq i \leq l} g_{0,i} \leq \sum_{1 \leq i \leq l} B_{0,i} \tag{21}$$

For the relay node with B_m, due to half-duplex, $g_m = R/2$. Thus $T_{min} \cdot R/2 \leq B_m$ or

$$T_{min} \leq \frac{B_m}{R/2} \tag{22}$$

Combining the Inequality 21 with the Inequality 22, we get $\sum\limits_{1 \leq i \leq l} g_{0,i} \leq \frac{R}{2}\frac{\sum_{1 \leq i \leq l} B_{0,i}}{B_m}$. Also, the sum of the rates from all children of the sink node should not exceed the radio capacity, which means $\sum\limits_{1 \leq i \leq l} g_{0,i} \leq R$. Thus, $\sum\limits_{1 \leq i \leq l} g_{0,i} \leq \min\{R, \frac{R}{2}\frac{\sum_{1 \leq i \leq l} B_{0,i}}{B_m}\}$.

For the sink node, $T_{min} \cdot \sum\limits_{1 \leq i \leq l} g_{0,i} \leq B_0$. Thus, the Max-Min network lifetime is $T_{mm} = \frac{B_0}{\min\{R, \frac{R}{2}\frac{\Sigma_{1 \leq i \leq l} B_{0,i}}{B_m}\}}$.

When the sink node do not have children acting as relay nodes, the Max-Min lifetime can be expressed as that in Theorem 1. This is because, the constraint of the inequality in Equation 18 only exists for the relay node and the problem is similar to that in Section 4.1 for this case.

An illustration can be made based on Figure 1. When we consider the half-duplex communication, the Max-Min network lifetime in the aggregation tree will become $T_m = \frac{13}{\min\{R, \frac{13}{7}\frac{R}{2}\}} = \frac{13}{\frac{13}{14}R} = \frac{14}{R}$.

5.3. Fairness of Rate Allocation

We define *one-hop-subtree* as a tree which is rooted at a child of the sink node. Suppose that the sink node (n_0) has l direct children, each denoted as $n_{0,i}(1 \leq i \leq l)$. Let the sum of the Geometry Bit Capacity of all the leaf nodes in a one-hop-subtree be denoted as $\sum_{s_k \in S_{n_{0,i}}} GB(s_k)$. We have:

Theorem 4. *To achieve fairness by the lexicographic method, the rate allocation strategy for all children $n_{0,i}(1 \leq i \leq l)$ of the sink node is as follows:*

$$g_j = \min\{\frac{R}{2}, \frac{\sum_{s_k \in S_{n_{0,i}}} GB(s_k)}{T_{mm}}\} \tag{23}$$

PROOF. For the one-hop-subtree which is rooted at $n_{0,i}$, the allocated rates for $n_{0,i}$ can be expressed as $\frac{\sum_{s_k \in S_{n_{0,i}}} GB(s_k)}{T_{mm}}$ (based on Proposition 3). Also, considering the constraint of half-duplex mode, the allocated rates for a relay node should be less than $R/2$. Thus, the rate allocated to node $n_{0,i}$ is $\min\{R/2, \frac{\sum_{s_k \in S_{n_{0,i}}} GB(s_k)}{T_{mm}}\}$.

Since there is only one one-hop-subtree with sum of data rates larger than $R/2$, it is only necessary to check the one-hop-subtree with the largest sum of Geometry Bit Capacity. If the root of that one-hop-subtree is a relay node ($n_{0,i}$) and the sum of its Geometry Bit Capacity satisfies $\sum_{s_k \in S_{n_{0,i}}} GB(s_k) > \frac{B_0}{2}$, then its aggregate rate should be $R/2$. Otherwise, the rate allocation strategy should follow that in Section 4.3.

Regarding the algorithms for computing Max-Min lifetime and fair rate allocation, the operation for leaf nodes is the same as that in Section 4.3. But for relay nodes and the sink node, due to half-duplex, the operations are different, as described in Algorithm 4 and Algorithm 5, respectively.

The relay nodes and the root node follow the similar procedure to obtain the Bit Capacity and Geometry Bit Capacity as that in Section 4.3, which is shown from line 5 to line 10 of Algorithm 2.

After obtaining the result of the computation, they report the result to their parent nodes for further iteration. A relay node also relays the multicast rate vector from its parents to its children. The root node calculates the optimal rate vector after obtaining information from all the leaf nodes (i.e., the source nodes), and then multicasts the fair rate allocation to all leaf nodes (line 13 of Algorithm 3).

Algorithm 4: Operations in Relay Node n_i for half-duplex case:

Initialization:
  E_i = getInitialEnergy(n_i);
  c_i = getPowDispPara(n_i);
  $B_i = GB(i) = \frac{E_i}{c_i}$;
On Receiving Reports $\{B_{d_k}, \{GB(s_j)|n_{s_j} \in \mathcal{S}_i\}\}$**:**
  $B_i = min\{B_i, \sum_{s_k \in \mathcal{S}_i} B_{s_k}\}$;
  Sort the members in $\{GB(s_j)|n_{s_j} \in \mathcal{S}_i\}$;
  $\{GB(j)\}$ = Sorted set in which $GB_{j-1} \leq GB_j$;
  $sum = 0$;
  for $k = 1$ **to** $|S_i|$ **do**
    $GB(k) = min\{GB(k), \frac{B_i - sum}{|S_i| - k + 1}\}$;
    $sum = sum + GB(k)$;
  Report $\{B_i, \{GB(s_k)\}\}$ to its parent;
On receiving allocated rate vector $\overline{g}$**:**
  Select the value of g_i from $\overline{g}$;
  if *n_i is the root of a one-hop-subtree and n_i is a relay node* **then**
    $sum = 0$;
    for $k = 1$ **to** $|\mathcal{S}_i|$ **do**
      $g_k = \min\{GB(k)/T_{mm}, \frac{g_i - sum}{|\mathcal{S}_i| - k + 1}\}$;
      $sum = sum + g(k)$;
  Multicast $\overline{g}$ to all children;

Theorem 5. Complexity*: Algorithms 4 and 5 have the time complexity of $\mathcal{O}(NlogN)$, and the message complexity of $\Theta(N)$.*

We skip the proof of this theorem since it is similar to the proof of Theorem 2.

Algorithm 5: Operations in the Root Node (Cluster Head) n_0 for half-duplex mode:

Initialization:
  Set value for E_i, c_i and B_0;
On Receiving Reports $\left\{B_{d_k}, \{GB(s_j)|n_{s_j} \in \mathcal{S}_0\}\right\}$**:**
  $B_0 = \min\{B_0, \sum_{s_k \in \mathcal{S}} B_{s_k}\}$;
  B_m = Maximum Bit Capacity of children which are also relay nodes;
  $T_{mm} = \frac{B_0}{\min\{R, \frac{R}{2}\frac{\Sigma B_{0,k}}{B_m}\}}$;
  Sort the elements in $\left\{\{GB(s_j)|s_j \in \mathcal{S}_{d_k}\}|d_k \in D_i\right\}$;
  $\{GB(j)\}$ = Sorted set in which $GB_{j-1} \leq GB_j$;
  $sum = 0$;
  for $k = 1$ **to** $|\mathcal{S}_0|$ **do**
    $GB_k = \min\{GB(k), \frac{B_0 - sum}{|\mathcal{S}_0| - k + 1}\}$;
    $sum = sum + GB(k)$;
  for $i = 1$ **to** l **do**
    $\sum_{s_k \in S_{n_{0,i}}} GB(s_k)$ = Sum of Geometry Bit Capacity of all leaf descendants of $n_{0,i}$;
    $g_i = \min\{R/2, \frac{GB(n_{0,i})}{T_{mm}}\}$;
  Multicast $\overline{g}$ to all children;

6. Discussion

For real implementation, the proposed algorithms should work over routing protocols which are based on the tree-topology. The algorithms do not decide the routing path, but calculate the optimal rates along the pre-built paths. We do not consider packet lost which is due to unreliable link conditions or interference. However, such challenge can be addressed by reliable data transmission mechanisms [27, 28] in MAC layer. Our algorithms do not discuss any specific reliable transmission mechanism and assume the rate vector will be received at the root node.

The proposed algorithms belong to proactive mechanism which means we decide the optimal data rates before traffic happens. This is different from traffic-aware rate control if we consider to shut down some flows and to admit others. Although the latter problem is interesting and complicated, it belongs to reactive mechanism which has also been studied in the literature.

We neglect the feed-back message in our problem modeling and algorithm derivations. The potential applications of our work is multimedia applications over WSNs, like image reconstruction, the feedback data (i.e. , acknowledgement message) rate is relatively small comparing to the image/audio/video data from sensor nodes to the sink node, and we just simply omit this part in our problem formulation. If we consider the feedback data (i.e. , ACK message), the formulation will be largely different from the current modeling and algorithms derivation. And we believe it deserves more efforts for a new research work.

Our works are based on the scenario of single sink node. However, it can be easily extended to the scenarios of hierarchically clustered topologies and multiple sink node, where the local cluster head or individual sink node calculate the optimal rates with their own clusters respectively.

7. Experimental Results

We evaluated the effectiveness of our algorithms through simulation-based experiments.

7.1. Experimental Settings

The settings of our experimental studies were as follows. We first generated an aggregation tree with a topology as illustrated in Figure 3. All nodes were distributed over a field of size $200mX200m$. The remaining energy of each node and the distance between two adjacent nodes were randomly generated.

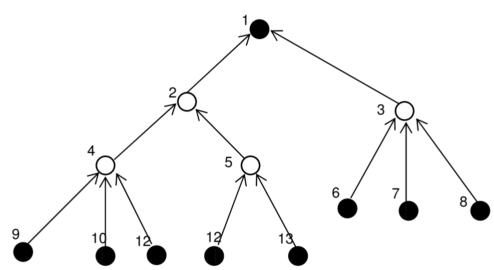

Figure 3: Experimental Topology

In our experiments, the distance between one node and its next hop node was randomly generated between $[15, 30]$(m). We also set $\alpha = 50nJ/b$, $\beta = 0.0013pJ/b/m^4$, and $m = 4$ for the power consumption model. The initial energy reserve of each sensor node was defined using a normal distribution with mean and variance of $(25J, 16J^2)$. The shared channel capacity (IEEE 802.15.4) was set to $128Kb/s$. This experimental configuration is consistent with that in [8].

7.2. Solution Space

To illustrate our solution strategy for the multi-objective programming problem, we show the entire solution space for the Full-Duplex mode in Figure 4. Each data point in the figure corresponds to one rate vector (for all source nodes). The value of network lifetime and the product of all source data rates were calculated for each vector.

We randomly generated 500 rate vectors for all nodes in Figure 3 and plot the Max-Min network lifetime T and $\prod_{s_k \in \mathcal{S}_0} g_{s_k}$ for all vectors. The distribution of the values of the two objectives are shown in Figure 4.

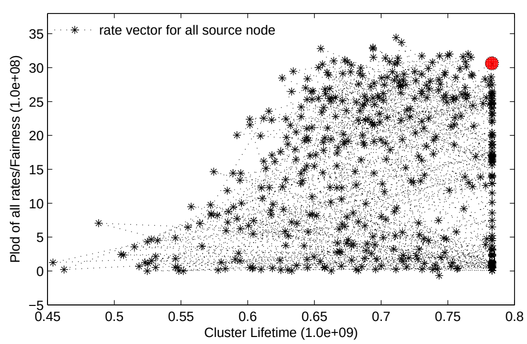

Figure 4: Solution Space for All Rate Vectors

Since the space of the entire solutions is a trade-off between Max-Min network lifetime and fairness, it is not always that a data point with Max-Min network lifetime also has the best fairness. Also, a data point with the highest value for fairness may not have the Max-Min lifetime. Thus, our goal is to find the vector point (marked by red color) in the most upper-right corner of Figure 4. This most upper-right point represents the rate vector with Max-Min network lifetime and maximized fairness under the given Max-Min lifetime.

7.3. Multiple Frequencies with Full-Duplex Mode

We show our rate allocation strategy in Figure 5 for the set of experiments that were conducted for this case. The rates were calculated based on the distributed algorithm in Section 4.3. By comparing with the Average Rate Allocation strategy in which all source nodes have same data rates, we observe that the rates in our strategy vary from node to node, since each node has a different Bit Capacity.

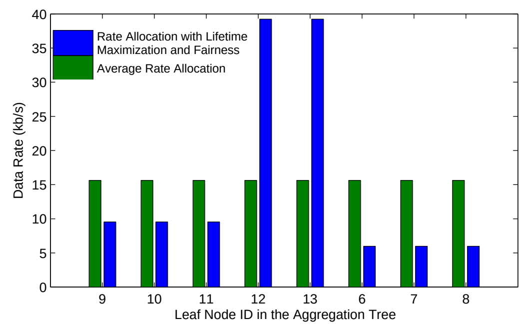

Figure 5: Data Rates for All Source Nodes

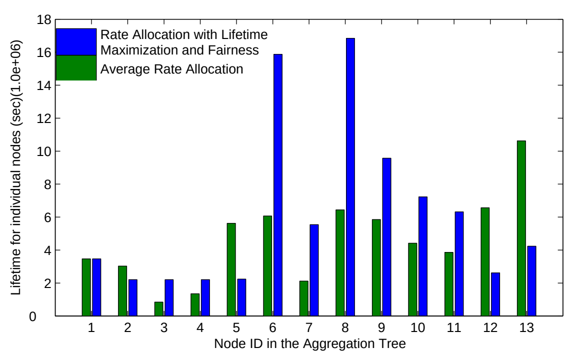

Figure 6: Individual Lifetimes for All Source Nodes

Figure 6 shows the individual lifetime for all sensor nodes. Recall that the network lifetime is defined as the smallest lifetime among all the nodes. From the figure, we observe that our rate allocation strategy achieves longer network lifetime than the average rate allocation strategy.

Figure 7 shows the lifetime of the same cluster when we change the node configuration with different remaining energy and transmission distance. The remaining energy and transmission distance of each node in different experiments has a normal distribution. We repeated the experiment 60 times, and obtained the maximum network lifetime in each experiment, both for our rate allocation strategy and the average rate allocation strategy.

From the figure, we observe that the maximum lifetime also has a normal distribution. In addition, our rate allocation strategy always achieves better performance than the average rate allocation strategy.

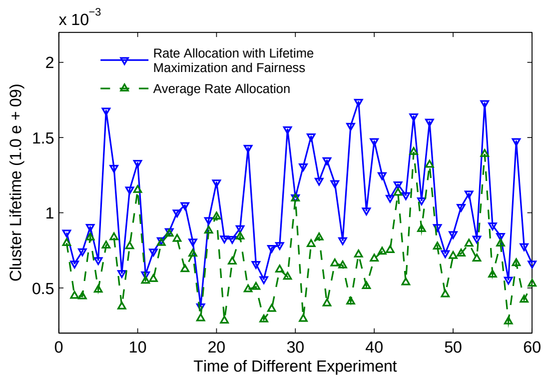

Figure 7: Network Lifetime in Different Experiments

7.4. Multiple Frequencies with Half-Duplex Mode

For the scenario of a node adopting multiple frequencies with half-duplex transmission mode (i.e., single transceiver), we simulated the Max-Min lifetime and fair rate allocation strategy over the same network topology as shown in Figure 3.

We show our rate allocation strategy in Figure 8. The rates were calculated based on the distributed algorithms in Section 5.3. We also compared the performance with that of the average rate allocation strategy. Due to the constraint of half-duplex transmission mode, the rate allocation for the average rate allocation strategy is different from that in the scenario of Full-Duplex transmission mode. In Figure 8, nodes 9 13 should have rates of $R/10$, and nodes 6 8 should have rates of $R/6$, so that the aggregated rates in every relay node do not exceed $R/2$.

We observe that the rates of our strategy vary from node to node and that the biggest individual rate is less than that of Figure 5, due to the constraint of Half-Duplex mode.

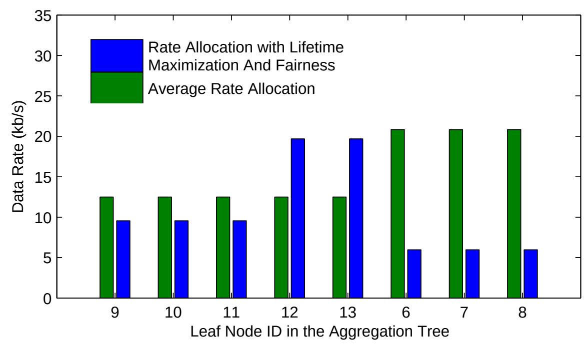

Figure 8: Data Rates for All Source Nodes

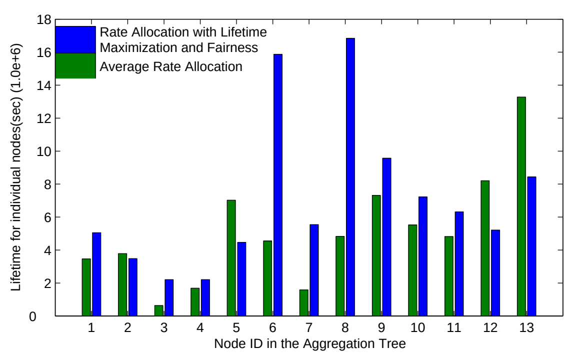

Figure 9: Individual Lifetimes for All Source Nodes

Figure 9 shows the individual lifetime for all sensor nodes. Recall that the network lifetime is defined as the smallest lifetime among all sensor nodes. From the figure, we observe that our rate allocation strategy achieves longer network lifetime than the average rate allocation strategy in Half-Duplex mode. Also, most of the nodes in Figure 9 achieved longer individual lifetimes when compared with that of Figure 6. This is because, in Half-Duplex mode, the source rate was slightly lower than that in Full-Duplex mode.

We also measured the lifetime of the same cluster under different configurations, as shown in Figure 10. We change the node configuration with different remaining energy and transmission distance with 60 times. The remaining energy and transmission distance of each node in different experiments has a normal distribution. The comparison was made between our rate allocation strategy and the average rate allocation strategy. From the Figure 10, we observe that the maximum lifetime also has a normal distribution and the proposed rate allocation strategy outperforms average rate allocation strategy.

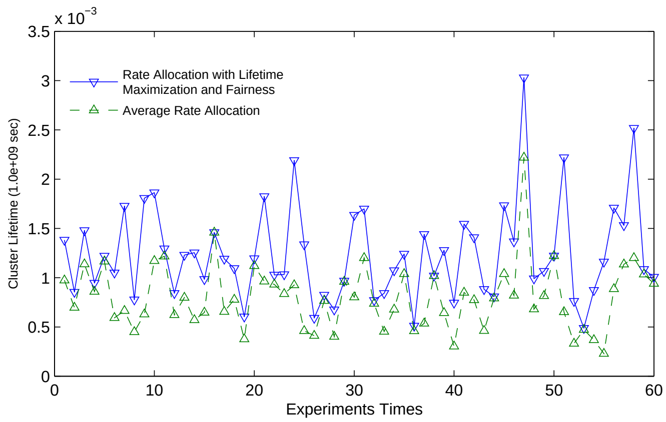

Figure 10: Comparison on Network Lifetime in Different Experiments

8. Conclusions

In this paper, we studied how to maximize the minimum (Max-Min) network lifetime and to achieve fairness with rate allocation for data aggregation applications in wireless sensor networks. Since the two objectives are generally correlated with each other and they usually cannot be maximized simultaneously, we adopt a lexicographic method to solve this multi-objective programming problem. Our method first determines the solution space of lifetime maximization, and then derives the optimal rate allocation strategy for ensuring fairness under that solution space. Two scenarios were considered: multi-frequency with full-duplex and multi-frequency with half-duplex. We also presented distributed algorithms to compute the maximum lifetime and the optimal rate vector for ensuring fairness for the two cases. The simulation results illustrated the effectiveness of the approach.

Several directions exist for further study, including rate allocation with multi-target tracking and multi-path routing for lifetime maximization and ensuring fairness.

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