

Analysis of Cluster Lifetime with Rate Allocation in Wireless Networks Subtitle as needed (paper subtitle)

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Abstract: We consider the rate allocation problem for data aggregation in wireless sensor networks with two objectives: 1) maximizing the lifetime of a local 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 maximum lifetime for the local aggregation cluster. 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. We also present low-complexity algorithms that a local aggregation cluster can use to determine the optimal rate allocation. Our simulation results validate our analytical results and illustrate the effectiveness of the approach.

Keywords: ANT, 802.15.4, BLE, WSN, MAC protocol

1. Introduction

We consider a wireless sensor network that is deployed in a strategic location for surveillance — e.g., tracking intruding targets [5]. Some nodes in the network generate physical measurements of an intruding target after sensing the presence of a target. A common operation on such tracking applications is data aggregation [9]. During aggregation, sensed data is gathered from different sensor nodes (i.e., source nodes) and is combined at a local cluster head. Source nodes may transmit sensed data via either one hop or multi-hop towards the cluster head. Generally, sensor nodes are battery-powered and consume energy in sensing, transmitting, and receiving data. The limited size of sensor nodes only allows for very limited energy storage and in most applications such as tracking, it is infeasible to recharge the node batteries. 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. An important approach for achieving energy efficiency is to control the data rates in the network- or upper layers. There are several reasons for doing so. For example, by controlling the data rates, network congestion can be controlled or even eliminated [4]. Congestion, if not controlled can impede the performance of applications with delay constraints, besides wasting transmission energy and radio resources due to retransmissions. Further, by controlling the data rates, the network's energy consumption can be balanced, and thereby the network lifetime can be maximized [16], [10]. For example, nodes with high remaining energy can be allowed to transmit more data, while those with low energy can be allowed to transmit less. Without such balanced energy consumption, some nodes may quickly exhaust their power, causing network partitions or malfunctions.

The requirement, from many data aggregation applications, is to achieve fairness [3], [4] among source

rates. 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. 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 [17], [11] between biased rate allocation (lifetime maximization) and even rate allocation (fairness). Thus, find a rate allocation strategy to achieve such trade-off is a challenge. In this paper, we formulate the above challenge as a multiobjective programming problem and adopt a lexicographic method [15] to solve the problem. First, we recursively induce the maximum possible 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. We also present a low-complexity algorithm to compute the maximum network lifetime and the optimal rate allocation for fairness. To the best of our knowledge, this is the first result on rate allocation in sensor networks that simultaneously maximizes network lifetime and fairness in data aggregation using a lexicographic method. The rest of the paper is organized as follows: In Section II, we overview the related work in rate allocation for sensor networks. In Section III, we present the network topology, transmission power model, and our problem formulation. In Section IV, we mathematically analyze the problem model and present our lexicographic solution. Section V describes our algorithms. We report our experimental results in Section VI, and conclude in Section VII.

2. Related Work

The problem of rate control and energy management in wireless sensor networks has been extensively studied. To maximize the network lifetime, Bhardwaj et al. [1] present a network lifetime upper bound for energy-efficient collaborative data gathering with optimal role assignments. Xue et al. [16] adopt a dual decomposition method to determine the optimal network lifetime for data aggregation in which source nodes have multiple routing paths to the sink node. In [13], Sankar et al. present a distributed algorithm with guaranteed approximation error for flow routing. In [7], Hou et al. study the max-min rate allocation among all nodes with a system lifetime requirement.

The problem of achieving fairness in rate allocation has also been well studied. For instance, achieving MAC-layer fairness among one-hop flows within a neighborhood is studied in [8]. In [14], the fair data collection problem with the NUM framework is studied. In [2], 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. Some previous efforts also consider both network lifetime maximization and fair rate allocation. In [11], Nama et al. present a general cross-layer framework that takes into account radio resource allocation, routing, and rate allocation for achieving trade-off between lifetime maximization and fairness. The authors solve the tradeoff problem via a dual decomposition method. In [17], the similar problem is addressed at the transport layer. The method 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 presenting fairness) and derive an optimal solution for maximizing the newly constructed function. The differences between our work and the above two works are: 1) we study the tradeoff problem in a local cluster which has a tree-like network topology that is more suitable for data aggregation. 2) We adopt a lexicographic method in which we prefer network lifetime maximization to fairness comparing with no preference in the existed works. This is because network lifetime is strongly correlated to energy consumption which is one of the most performance-critical aspects of sensor networks.

3. Network Topology and Problem Model

3.1 Network Topology

The network topology for data aggregation is a tree structure (aggregation tree). We have three types of sensor nodes in the network: source nodes, relay nodes, and the cluster head (i.e., root node in the aggregation tree). 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 (root node). The cluster head is the aggregation

end point. For this network topology for data aggregation, we make the following assumptions: (1) All sensor nodes and the cluster head are time-synchronized; (2) Any sensor nodes at most has 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 (targets) and transmit the sensed data to the cluster head simultaneously. We also assume that interference and hidden terminal problem at relay nodes/cluster head can be avoided by virtual carrier sensing via RTS/CTS mechanism in IEEE 802.15.4 CSMA/CA protocol which is widely adopted by the MAC protocol (i.e., S-MAC or B-MAC) for sensor networks. And 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

For a sensor node, the power consumption due to data communication (i.e., receiving and transmitting) is the dominant factor. Suppose there are N sensor nodes in a cluster. Each node is denoted as n_i ($i \in N$). We denote $g_{i,j}$ 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.

3.3 Motivation

Radio communication quality between low power sensor devices is affected by spatial and temporal factors. The spatial factors include the surrounding environment, such as terrain and the distance between the transmitter and the receiver. Temporal factors include surrounding environmental changes in general, such as weather conditions. In this section, we present experimental results for investigation of these impacts.

We note that previous empirical studies on communication reality [3] [4] [5] [10] [12] [2] suggest that for a specified transmission power, fixed communication distance, and antenna direction, the received signal power and the link quality vary. But they do not focus on a systematic study of the radio and link dynamics when different transmission powers are considered. We conducted these measurements, and we are the first to study systematically the spatial and temporal impacts on the correlation between transmission power and Received Signal Strength Indicator (RSSI)/ Link Quality Indicator (LQI) [15]. Both RSSI and LQI are useful link metrics provided by CC2420 [7]. RSSI is a measurement of signal power which is averaged over 8 symbol periods of each incoming packet.

4. Link Quality Threshold

Wireless link quality refers to the radio channel communication performance between a pair of nodes. PRR (packet reception ratio) is the most direct metric for link quality. However, the PRR value can only be obtained statistically over a long period of time. Our experiments indicate that both RSSI and LQI can be used effectively as binary link quality metrics for transmission power control. Guided by the observations obtained from empirical experiments, in this section, we propose our Adaptive

Transmission Power Control (ATPC) design. The objectives of ATPC are to make every node in a sensor network find the minimum transmission power levels that can provide good link qualities for its neighboring nodes, to address the spatial impact to dynamically change the pair wise transmission power level over time, to address the temporal impact.

5. Algorithms

Based on the problem formulation and the lexicographical solution, we present an algorithm to compute the lifetime and the fair rate allocation. The algorithms contain both distributed part and centralized part. The intermediate roots of different subtrees will distributively calculate BitCapacity and 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. It has the lowest computational complexity.

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

- 1: Initialization:
- 2: $E_i = \text{getInitialEnergy}(n_i)$;
- 3: $c_i = \text{getPowDispPara}(n_i)$;
 $B_i = FB(i) = E_i$
 c_i
- 4: ;
- 5: Report fB_i ; $fFB(i)$ to its parent node;
- On receiving multicasted rate allocation vector $g = fgsk6$: g
- If $sk = i$, set $gi = gsk7$: .

Algorithm 2: Operations in Relay Node n_i :

- 1: Initialization:
- 2: Set value for E_i , c_i and B_i ;
- On Receiving Reports
- ©
- $Bdk; fFB(s_j)jsj2 Sdkgjdk2 Di$
 a
- 3: ;
- $B_i = \min fB_i$;
- P
- $sk2Si$
- $Bsk4: g$;
- Sort the members in
- ©
- $fFB(s_j)jsj2 Sdkgjdk2 Di$
 a
- 5: ;
- 6: $fFB(j)g =$ The sorted set in which $Bj_1 \cdot Bj_j$;
- 7: $sum = 0$;
- 8: for $k = 1$ to $jSijdo$
- $FB(k) = \min fFB(k); B_i; sum$
- $jSij9: g$;
- 10: $sum = sum + FB(k)$;
- 11: Report fB_i ; $fFB(sk)g$ to the parent node;
- 12: On receiving multicasted rate vector g ;
- 13: Forward the information to all subtrees via multicast;

6. Experimental Results

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

generated an aggregation tree with a topology as illustrated in Figure. 3. The number of children of non-leaf nodes was randomly distributed

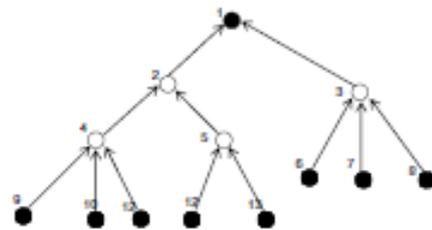


Figure 1: Topology in Experiments

The distance between one node to its next hop node was also randomly generated between [15; 30] (m). In our experiments, we set $\alpha = 50nJ=b$, $\tau = 0:0013pJ=b=m4$, 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 $(25J; 16J2)$. The shared channel capacity (IEEE 802.15.4) is set to $128Kb=s$ in our experiment.

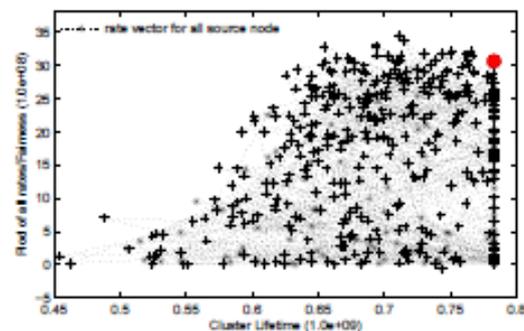


Figure 2: Topology in Experiments and Solution Space for All Rate Vectors

To illustrate our solution strategy for the multi-objective programming problem, we show the entire solution space 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.

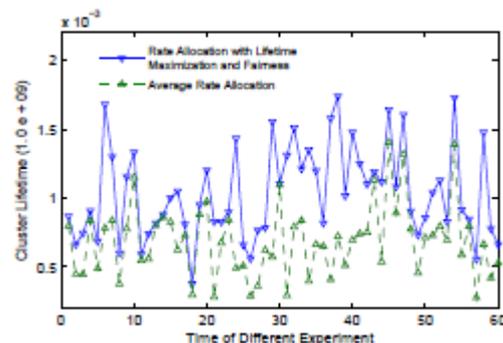


Figure 3: Network Lifetime in Different Experiments

Figure 3 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 for 60 times, and drew the maximum network lifetime in each time

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.

7. Conclusions

This paper studies how to maximize the cluster lifetime and to achieve fairness with rate control for data aggregation applications on sensor networks. To solve the multi-objective programming problem, we adopt a lexicographic method by first determining the solution space of lifetime maximization and then deriving the optimal rate allocation strategy for fairness under that solution space. We also present low-complexity algorithms to compute the maximum lifetime and the optimal rate vector for fairness. The simulation results illustrate 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 fairness.

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