Energy Efficient Multi-mode Operation for Networked Wireless Sensors*

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Abstract

This paper aims at developing a comprehensive model for optimal multi-mode wireless sensor operations. We start by proposing a maximum data retrieval (MDR) problem that jointly optimizes the routing and scheduling decisions over time for multi-mode wireless sensors. Attempting to solve the general yet extremely complex problem leads to observations and analysis of optimal store-and-forward (S&F) operations for individual sensors in an ideal setting. Our analytical model for the S&F operation provides not only closed form expressions in estimating sensor lifetime and total transmission, but also insights on developing a simpler flow distribution problem that could approximate the MDR problem. Heuristic procedures are then developed to demonstrate the feasibility of having the sensors perform in S&F cycles. Our simulation shows that these heuristics achieves performance close to theoretical estimates derived based on the S&F operation analysis.

1. Introduction

The emergence of wireless sensor networks (WSN) [1, 2] introduce an exciting new frontier for data sensing, data transfer, and data retrieval applications. Various tracks of research work, ranging from device engineering to network protocol design, have been initiated to address the fundamental problem of constrained energy for networked wireless sensors. One common direction among this cross-disciplinary effort is the use of wireless sensors that can operate in multiple modes, e.g., sleep, idle, receive, and transmit. The idea behind multi-mode wireless sensors is to preserve the energy consumption when one or more of the sub-components are not in use.

Among the various research tracks, network engineers and computer scientists focus on determining when and how to operate the wireless sensors in different modes so that the network as a whole can achieve better performance. Among others, authors in [3] and [4] propose TDMA-based and CSMA/CA-based schemes, respectively, to determine the sensor transmission schedule and thereby when to turn off the communication component of the sensors. Particularly in [4], the proposed Sensor-MAC protocol determines the sleep schedules of a sensor node based on the schedule of its neighbors, and exhibits good energy savings over schemes that have the sensors remain on at all times. Various other MAC propocols have also been proposed, e.g., [5, 6, 7], and authors of [8] and [9] have discussed scheduling from the topology control perspective. The above set of work, however, either overlooks the impact of the buffer size of the sensor and the energy spikes incurred due to switching between the operational modes, or lacks the theoretical foundation for the choice of policies that are used to determine the transmission schedule of the sensors. In addition to scheduling sensor operations, routing is another aspect in retrieving sensed data from individual wireless sensors to the data processing center. Unfortunately, to our knowledge, none of the existing routing approaches for wireless sensor networks, e.g., [10, 11, 12, 13], have truly taken the multi-mode operations into account.

One missing piece in the various afore-mentioned efforts is a formal model that jointly optimizes the routing and the scheduling decisions for networked multi-mode wireless sensors. Notice that research effort has been put forth to jointly optimize fusion and routing decisions [14], and to jointly optimize transmission power control and routing decisions [15, 16]. These studies, due to the complexity introduced, can only focus on determining steady state "flow distributions" over the network, which does not directly translate to online policies. By contrast, our approach attempts to determine the exact sequence of transmissions and the path to forward sensed data over time. We do not claim that we can solve our proposed joint optimization model to its entirety. Instead, this paper starts by analyzing how complex the problem can be and focuses on breaking down the problem, hoping to develop a practical online policy that also has theoretical supports.

The contribution and organization of this paper are as follows. In the next section, we will first develop a joint routing and scheduling optimization problem by accounting for

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both network spatial reuse constraints and various multi-mode sensor operation constraints. Section 3 will follow and provide an in-depth analysis of the optimal schedule an individual sensor can have in an ideal setting. The development of the optimal schedule opens up a new avenue to tackle the overall joint optimization problem, and provides theoretical estimates of wireless sensor network performance. Heuristic procedures are proposed in Section 5 to investigate whether and how one can achieve performance close to the theoretical estimates. Concluding remarks will be provided in Section 6

2. The Maximum Data Retrieval Problem

The data retrieval problem is to determine when and which path to transmit and forward sensed data from individual sensors over possibly multiple intermediate nodes to reach a data processing center. More specifically, the problem is a joint optimization of scheduling and routing decisions subject to flow conservation, energy and spatial reuse constraints, which will be formally defined later in this section. Note that there are two other design decisions affecting the data retrieval process: in-network data fusion and transmission power control. We, however, consider modeling the most basic wireless sensor nodes, which are not able to perform in-network data fusion or dynamically adjust their transmission powers. In addition, our focus is on determining the exact sequence of wireless transmissions over time.

The first challenge of modeling the joint optimization problem is to understand the various operational modes of wireless sensors, and to properly define the optimization variables. Modern wireless sensors are made up of many components, including processing unit(s), sensing device(s), and RF circuitry. These components may operate either independently or as a whole in different modes - sleep, idle, receive, transmit, etc. [17, 18, 19]. Many commercial wireless sensor data specifications [19, 18, 20] suggest that the difference in the power consumption between the idle and the receive mode is marginal. Therefore, we decided to model the wireless sensors with three basic operational modes: sleep, receive, and transmit, where the receive mode refers to the case where the transceiver is on but not transmitting, regardless of whether it is actually receiving or in the idle mode. When switching between the operational modes, the RF transceiver is likely to incur an energy spike [21]. We consider two energy spikes: one incurred when turning on the transceiver from the sleep mode, and the other incurred due to powering up the transmitter to actually transmit.

Now we may formally define our model. Consider a network formed by a set of sensor nodes N. A sensor j can receive messages from node i if and only if j is a neighbor of i, denoted as $j \in N(i)$. We assume symmetric wireless links between nodes, so $j \in N(i)$ if and only if $i \in N(j)$. Note that different physical wireless transmission property may define different $N(i)$'s. Our approach is independent of how the neighborhood is defined, as long as it does not change over time. Let S be the set of sinks, each of which is a candidate of the destination of any sensed data. We do not restrict the sink to which the sensed data should go. Instead, we assume there is a backbone network that interconnects the sinks and the sensed data will be processed on or beyond this backbone network. Every sensor node has a buffer size (b_i), an average sensing rate (λ_i), a total initial energy (e_i^{tot}), the power levels to operate in the sleep mode (p_i^s), the additional power needed to turn on the RF transceiver (p_i^r), the additional power needed to transmit (p_i^t) at a rate (c_{ij}) to neighbor j, and the energy spikes incurred when transitioning from the sleep mode to the receive mode (e_i^{sr}) and that from the receive mode to the transmit mode (e_i^{rt}). Note that, based on the defined power parameters, the power consumed while operating in the sleep, receive, and transmit modes for node i are p_i^s, $p_i^s + p_i^r$, and $p_i^s + p_i^r + p_i^t$, respectively.

Based on these definitions, we developed a mixed-integer programming problem that maximizes the total data retrieved by the sinks until one of the sensors dies due to energy exhaustion[1]. We refer to this problem as the Maximum Data Retrieval (MDR) problem, as shown in Figure 1. A summary of the notations is given in Table 1.

The model essentially determines the time intervals T_k, during which a subset of sensor nodes transmit data to their neighbors. Constraints (1a), (1b) and (1c) determine whether sensor i transmits to sensor j at time k (X_{ijk}), as well as the amount of time for such a transmission (F_{ijk}). Similarly, constraints (2a), (2b) and (2c) determine if the communication module of sensor i is in the receive (idle) mode at time k (Y_{ik}) along with the amount of time the module is in the receive mode (G_{ik}).

The strengths of our model are the accountability of the spatial reuse on the network, the energy consumption due to changes between the operational modes (sleep-to-receive and receive-to-transmit), as well as the store-and-forward capability of the sensors over time. Constraint (3a) prevents a sensor from transmitting and receiving during the same time interval. Constraints (3b) and (3c) prevent the neighbors of each transmitter from receiving, and the neighbors of each receiver from transmitting. Note that by altering the set of $N(i)$, one can change the spatial reuse constraints to account for a different wireless signal interference model. Constraint (4a) forces the communication module to be on, if the corresponding sensor at the time interval k is either transmitting or receiving. It is important to note that a communication module could still be on, even if the sensor is neither receiving nor transmitting. This will occur if the expenditure of energy for a time period is less than the cost of switching the

1 We recognize that defining the network lifetime as the time till the first sensor dies may not be representative to all sensor networks. This definition, however, is sensible if every sensor is critical and has been used by many researchers, e.g., [15].

$$
\begin{array}{rcll}
\multicolumn{4}{l}{\max \sum_{i\in S}\sum_{j\in N(i)}\sum_{k=1}^{K} F_{jik}c_{ji}} \\
\multicolumn{4}{l}{\text{subject to}} \\
F_{ijk} & \leq & T_k & \forall i\in N,\ j\in N\cup S,\ 1\leq k\leq K \quad (1a)\\
F_{ijk} & \leq & M\cdot X_{ijk} & \forall i\in N,\ j\in N\cup S,\ 1\leq k\leq K \quad (1b)\\
F_{ijk} & \geq & T_k - M(1-X_{ijk}) & \forall i\in N,\ j\in N\cup S,\ 1\leq k\leq K \quad (1c)\\
G_{ik} & \leq & T_k & \forall i\in N,\ j\in N\cup S,\ 1\leq k\leq K \quad (2a)\\
G_{ik} & \leq & M\cdot Y_{ik} & \forall i\in N,\ j\in N\cup S,\ 1\leq k\leq K \quad (2b)\\
G_{ik} & \geq & T_k - M(1-Y_{ik}) & \forall i\in N,\ j\in N\cup S,\ 1\leq k\leq K \quad (2c)\\
\sum_{j\in N(i)} X_{ijk} + \sum_{j\in N(i)} X_{jik} & \leq & 1 & \forall i\in N,\ 1\leq k\leq K \quad (3a)\\
\sum_{j\in N(i)}\sum_{l\in N(j)-i} X_{ljk} - M(1-\sum_{j\in N(i)} X_{ijk}) & \leq & 0 & \forall i\in N,\ 1\leq k\leq K \quad (3b)\\
\sum_{j\in N(i)}\sum_{l\in N(j)-i} X_{jlk} - M(1-\sum_{j\in N(i)} X_{jik}) & \leq & 0 & \forall i\in N,\ 1\leq k\leq K \quad (3c)\\
Y_{ik} - (\sum_{j\in N(i)} X_{ijk} + \sum_{j\in N(i)} X_{jik}) & \geq & 0 & \forall i\in N,\ 1\leq k\leq K \quad (4a)\\
Z_{ik} - (\sum_{j\in N(i)} X_{ijk} - \sum_{j\in N(i)} X_{ijk-1}) & \geq & 0 & \forall i\in N,\ 2\leq k\leq K \quad (4b)\\
W_{ik} - (Y_{ik} - Y_{ik-1}) & \geq & 0 & \forall i\in N,\ 2\leq k\leq K \quad (4c)\\
\sum_{l=1}^{k}\sum_{j\in N(i)} c_{ij}F_{jil} + \sum_{l=1}^{k}\lambda_{il}T_l - \sum_{l=1}^{k}\sum_{j\in N(i)} c_{ij}F_{ijl} & \leq & b_i & \forall i\in N,\ 1\leq k\leq K \quad (5a)\\
\sum_{l=1}^{k}\sum_{j\in N(i)} c_{ij}F_{jil} + \sum_{l=1}^{k}\lambda_{il}T_l - \sum_{l=1}^{k-1}\sum_{j\in N(i)} c_{ij}F_{ijl} & \geq & \sum_{j\in N(i)} c_{ij}F_{ijq} & \forall i\in N,\ 1\leq k\leq K \quad (5b)\\
e_i^{sr}\sum_{k=1}^{K} W_{ik} + e_i^{rt}\sum_{k=1}^{K} Z_{ik} + p_i^{s}\sum_{k=1}^{K} T_k + p_i^{r}\sum_{k=1}^{K} G_{ik} + p_i^{t}\sum_{k=1}^{K}\sum_{j\in N(i)} F_{ijk} & \leq & e_i^{tot} & \forall i\in N \quad (6)
\end{array}
$$

Figure 1. The Maximum Data Retrieval (MDR) model for networked multi-mode wireless sensors.

transceiver from off to on. Constraints (4b) and (4c) allow the model to track the energy spikes due to switching from sleep to receive (W_{ik}) and from receive to transmit (Z_{ik}), respectively. Constraints (5a) and (5b) prevent the buffer from overflowing and ensure that the amount of transmitted data does not go beyond what has been sensed and received (as a relay node in the multi-hop network). Finally Constraint (6) decrements the energy accordingly due to the operational modes in each time interval and the energy spikes, and guarantees that the amount of energy to be consumed over time will not exceed the total available energy on the sensor.

The MDR problem explicitly determines the sensor operation schedules, and implicitly forces the sensed data to take energy efficient paths to reach the sinks, which have infinite energy and infinite buffer. The integer decision variables clearly increase the complexity of the model. Yet, the complexity is unavoidable since the model decides on the exact sequence of operations of all sensors over the network lifetime, while account for the restricted spatial reuse. As expected, the computational complexity (NP-Hard since it is a generalization of Vertex Covering) of the problem prevents the use of optimization tools to obtain solutions in a reasonable time. In our attempts in solving the MDR problem optimally using CPLEX, we observed that most wireless sensor nodes in the network tend to operate in periodical (or semi-periodical) "store-and-forward" cycles. This creates the need to develop practical heuristic procedures that find "good" solutions efficiently. The next section analyzes this store-and-forward operation schedule that seemingly leads to maximum amount of sensed data retrieved.

3. Optimal Store and Forward Cycle

One key challenge in the MDR problem is to determine the sensors' operation schedule (sleep, receiving and transmission) subject to the spatial reuse constraints. Research efforts have attempted to formulate and solve the "scheduling" problem, e.g., [22, 23]; yet, to our knowledge, no complete answer has been put forth for general networks in the dynamic regime. This study takes a different approach than existing ones, and examines what the best possible operation schedule could be for individual sensors assuming an ideal

Parameters	Definition
N	the set of sensor nodes
S	the set of sink nodes
$N(i) \subseteq N \cup S$	the set of 1-hop neighbors of node i
$c_{ij} > 0$	the transmission capacity between node i and node j
$b_i > 0$	the buffer size of node i
λ_i	the sensing event arrival rate to node i
$e_i^{tot} > 0$	the total amount of energy available for node i
$e_i^p > 0$	the spike energy consumed for node i to switch from sleep to receive or from receive to transmission mode
$p_i^s > 0$	the power level for node i to stay in the sleep mode
$p_i^r > 0$	the power (in addition to p_i^s) for node i to stay in the receive mode
$p_i^t > 0$	the power (in addition to $p_i^s + p_i^o$) for node i to stay in the transmission mode
$M > 0, K > 0$	a large value, the number of time intervals
Variables	**Definition**
$T_k \geq 0$	the duration of the k^{th} time interval
$F_{ijk} \geq 0$	the time duration during which node i transmits to node j within the k^{th} time interval
$G_{ik} \geq 0$	the time duration node i turns on the communication circuit within the k^{th} time interval
$X_{ijk} \in \{0,1\}$	1 if node i transmits to node j during the k^{th} time interval and vice versa
$Y_{ik} \in \{0,1\}$	1 if node i turns on the communication circuit during the k^{th} time interval and vice versa
$W_{ik} \in \{0,1\}$	1 if node i switches from sleep to receive at the beginning of the k^{th} time interval, and 0 otherwise
$Z_{ik} \in \{0,1\}$	1 if node i switches from receive to transmit at the beginning of the k^{th} time interval, and 0 otherwise

Table 1. Variable/parameter definitions for the integer-programming model.

situation. More specifically, we consider that a wireless sensor can transmit and receive whenever it wants, and data is always available. The idea behind this approach is that upon determining the "ideal" schedule, we may simplify the MDR problem and investigate an approximately optimal yet practical solution.

We will use the same buffer, power and energy parameters defined in Table 1, but eliminate the use of sub-index i since the following analysis focuses on an individual wireless sensor node. To distinguish between data arriving to the wireless sensor via the sensing unit and data arriving via the RF receiver, we use λ_s and λ_r to represent the average sensing rate and the average receiving rate, respectively, and μ is the transmission capacity.

Notice that data may arrive in packets or through sensed whenever an event happens, instead of a constant flow of bit streams. In the case where the operation (sleep, receive and transmit) intervals are much larger than the time scales to perform packet transmission and event sensing, the average rates are more than appropriate to be used for deriving the amount of data arrived in that interval. In light of considering a continuous monitoring sensor network, we assume that the sensing device will be kept on at all times and the amount of data sensed in any large enough time interval t will be $\lambda_s t$. The transceiver, however, can be turned on and off and, while on, it can either receive or transmit but not both at the same time[2]. Therefore, while the average amount of data received by the sensor node in a "large-enough" time interval t is $\lambda_r t$, the actual time it takes to receive the data depends on the transmission capacity of the neighbor nodes of the sensor. For simplification, we assume a homogeneous environment where all neighbor nodes will have the same transmission capacity μ as the node of interest does. That is, the time it takes to receive $\lambda_r t$ units of data will actually be $\frac{\lambda_r t}{\mu}$.

Consider a busy cycle during which the buffer is empty only at the beginning and at the end of the cycle. The following discussion focuses on determining the most amount of data that can be transmitted by a wireless sensor using the least amount of energy during a busy cycle. Recall the assumed ideal case where the sensor node can transmit and receive whenever it wants and data is always available to be received and sensed. It should be clear that, based on this assumption, the sensor will schedule its transmission once and only once immediately following the reception and sensing that accumulates data in the buffer. Consequently, there will be exactly one e^{rt} and at most one e^{sr} incurred. Figure 2 depicts an exemplary buffer usage over a busy cycle based on the scenario described above. Notice that within this busy cycle, the data is stored and then forwarded; therefore, we refer to it as the store-and-forward (S&F) cycle.

The S&F cycle shown in Figure 2 starts with the sen-

2 A wireless sensor may be able to transmit and receive at the same time, if multiple antennae and circuits are used. We, however, do not consider such expansive wireless sensors in this paper.

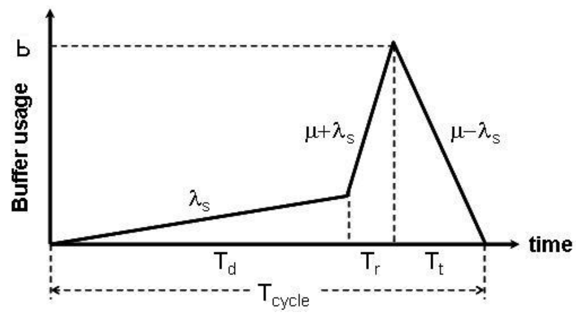

Figure 2. Buffer usage of a wireless sensor over an ideal busy cycle.

sor collecting data only via sensing with a rate of λ_s for T_d amount of time. Following sensing, the buffer usage increases at a rate of $\mu + \lambda_s$ by performing both receiving and sensing at the same time - recall that the data is received at rate μ. After T_r amount of time, the buffer is full and the sensor starts to transmit what has been stored and that continuously arrives via sensing. In this transmission phase, the buffer usage decreases at a rate of $\mu - \lambda_s$. Note that during the first T_d time interval, the sensor may choose to be in the sleep mode, or to stay in the receive (idle) mode to avoid the penalty of incurring an energy spike e_{sr}.

Now let's consider the stability condition for this S&F cycle. A periodical operation with the S&F cycle is stable if the buffer usage does not go beyond the buffer size b and will go down to zero at the end of the cycle. Based on these two constraints and the fact that transmission and receiving cannot happen simultaneously, we derive the following stability condition.

Lemma 1 *The S&F cycle is stable if and only if* $\lambda_s + 2\lambda_r \leq \mu$.

Proof: The stability condition follows by solving the following equality and inequalities.

$$\begin{aligned} T_{cyc} &= T_d + T_r + T_t \\ T_{cyc}\lambda_r &= T_r\mu \\ T_{cyc}\lambda_s + T_r\mu - b \leq T_t\mu &\leq T_{cyc}\lambda_s + T_r\mu \end{aligned}$$

■

Note that this stability condition is more restricted than "$\lambda_s + \lambda_r \leq \mu$" for traditional flow models where transmission and receiving can happen simultaneously.

Satisfying the stability condition, we can now solve for, within a S&F cycle, the amount of data transmitted (R_{cyc}), the amount of energy used (E_{cyc}) and the time interval of the S&F cycle (T_{cyc}). First, the total data that can be transmitted in a S&F cycle is what can be transmitted in an interval of $\frac{b}{\mu-\lambda_s}$ with transmission rate of μ. This gives

$$R_{cyc} = \frac{b \cdot \mu}{\mu - \lambda_s} \tag{1}$$

Since the total rate of data arriving to the sensor, either via sensing or receiving, is $\lambda_s + \lambda_r$, and the total transmitted data in the time interval T_{cyc} is R_{cyc}, we have

$$T_{cyc} = \frac{b \cdot \mu}{(\mu - \lambda_s)(\lambda_s + \lambda_r)} \tag{2}$$

Furthermore, notice that the sensing power p^s will be consumed during the entire T_{cyc} interval, additional power p^r will be consumed during the T_r time interval and possibly the T_d interval if e^{sr} is large, and the transmit power p^t will be consumed during the T_t interval. This gives the closed form expression for the energy used during a S&F cycle as shown below.

$$\begin{aligned} E_{cyc} = {} & \frac{b \cdot p^s \cdot \mu}{(\mu - \lambda_s)(\lambda_s + \lambda_r)} + \frac{b \cdot p^r \cdot (\lambda_s + 2\lambda_r)}{(\mu - \lambda_s)(\lambda_s + \lambda_r)} + \frac{b \cdot p^t}{(\mu - \lambda_s)} \\ & + \min\left(e^{sr}, \frac{b \cdot p^r \cdot (\mu - \lambda_s - 2\lambda_r)}{(\mu - \lambda_s)(\lambda_s + \lambda_r)}\right) + e^{rt} \end{aligned} \tag{3}$$

The above equations allow one to analyze the lifetime of a wireless sensor node given the total initial energy e^{tot} available to the sensor. Notice that Equations (1), (2) and (3) correspond to the case where most amount of data is transmitted using least amount of energy in a busy S&F cycle. This observation leads to the theorem below that finds the upper bounds for the lifetime of the sensor node and the total amount of data that can be transmitted during this lifetime.

Theorem 1 *The lifetime (T_{life}) and total amount of data transmitted (R_{life}) of an individual sensor with initial energy $e^{tot} \gg E_{cyc}$ will be upper bounded based on the following inequalities, respectively.*

$$T_{life} \leq \frac{e^{tot}}{E_{cyc}} \cdot T_{cyc} := T^*_{life} \tag{4}$$

$$R_{life} \leq \frac{e^{tot}}{E_{cyc}} \cdot R_{cyc} := R^*_{life} \tag{5}$$

The proof of Theorem 1 lies in the fact that $\frac{R_{cyc}}{E_{cyc}}$ gives the most energy efficient bits per joule transmitted by an individual sensor. Now with a total available energy e^{tot} that is much larger than E_{cyc}, one cannot transmit more than $\frac{e^{tot}}{E_{cyc}} \cdot R_{cyc}$ amount of data. The lifetime also follows. Note that the inequalities shown in Theorem 1 become equal if E_{cyc} exactly divides e^{tot}. Since we assume $e^{tot} \gg E_{cyc}$, we can approximate a sensor node's lifetime and the total amount of data transmitted over the lifetime as T^*_{life} and R^*_{life}, respectively.

4. Model Analysis and Discussion

A logical question following the S&F model is whether the suggested ideal S&F cycle will be feasible for all nodes in a given network. For arbitrary networks, the answer is no! Figure 3 shows an exemplary network where not all the nodes in the network can operate in S&F cycles. It is unavoidable for this network, that at least one of the three level-2 nodes, which transmissions may interfere with each other, needs to switch from the sleep to the transmit mode twice in a single operation cycle; Otherwise, the sink node will need to turn on the transceiver more than once to receive data from the level-2 nodes.

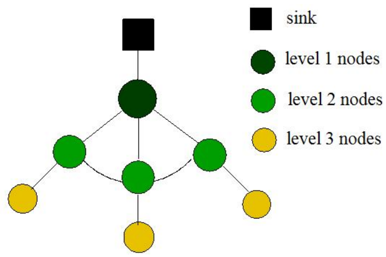

Figure 3. An exemplary network where not all the nodes in the network can operate in S&F cycles.

Since that in general the S&F cycles are not always feasible for all nodes, we propose to identify the nodes that have determining impact on the lifetime and the total retrieval of the entire network, and let them have the priority to operate in S&F cycles. Below we use the S&F model developed in Section 3 to characterize different types of sensor nodes in a network, so as to determine their roles and possibly obtain insights to find approximate solutions for the MDR problem.

4.1. Lifetime Critical Nodes

We first identify the nodes that may exhaust their battery energy first and consequently determine the lifetime of the entire network. Recall Equations (2), (3) and (4). These equations suggest that, given the physical make-up of a wireless sensor node (i.e., the transmission capacity, the buffer size, and the various energy power parameters are determined), a node's lifetime depends solely on λ_{r} and λ_{s}. Furthermore, since it is logical to deploy same type of sensors on a sensing field uniformly (or at least attempting to be uniformly), it is reasonable to assume that the above parameters as well as the average sensing rate are about the same for all sensors. In this case, λ_{r} is the determining factor of a sensor's lifetime, and the larger it is the shorter the lifetime. Consider the network environment defined in Section 2, it is not difficult to see that the nodes that are one hop away from the sinks (i.e., $\{n \in N(S)\}$) are the ones that will exhaust their energy the earliest[3], since all sensed data goes through them and this translates to huge λ_{r}.

3 Similar observation of that the 1-hop sensors being the bottleneck for network lifetime has been made in [15].

Since the nodes in $N(S)$ are critical to the network lifetime, it makes sense to have them operate in the ideal S&F cycles, while letting others transition between operational modes more often. This implies that a possible approximated solution to the MDR problem may be found by determining the flow distribution over the entire network (i.e., finding $\lambda_{\mathrm{r},i},\ \forall i \in N$) that minimizes the lifetime of only the nodes in $N(S)$. The lifetime of these 1-hop nodes can be modeled using T^*_{life} from Equation (2). It is still an open problem of how exactly this flow distribution problem can be formulated so that it is easy to be solved while guarantying reasonable closeness to the MDR problem.

4.2. Energy Inefficient Nodes

The nodes that are far away from the sinks, though not critical to the lifetime of the entire network, turn out to use energy relatively less efficient than those closer to the sink. This general statement can be explained by considering a chain of n sensor nodes, indexed as 1, 2, ..., n to indicate the number of hops each node is away from the sink. Note that in this chain network, all nodes can operate in a global S&F cycle. The global S&F cycle requires that node $i+1$'s transmission schedule matches node i's receiving schedule, and so on. Based on this requirement, the effective buffer size that can be used by a node diminishes as the node is situated farther away from the sink. Assuming that the physical buffer size is b, node 1 in the chain network can use the entire buffer size, $b^*_1 = b$, but the subsequent nodes can use only buffer size b^*_i as given below.

$$b^*_i \quad = \quad b^*_{i-1} \times \frac{(\lambda_{\mathrm{r},i} + \lambda_{\mathrm{s},i})(\mu - \lambda_{\mathrm{s},i})}{(\lambda_{\mathrm{r},i-1} + \lambda_{\mathrm{s},i-1})(\mu - \lambda_{\mathrm{s},i-1})}, \quad \forall i = 2, \ldots, n.$$

Because of the diminishing buffer size, the nodes that are far away from the sink cannot store much data before forwarding it. Consequently, the energy spikes become a bigger portion of the energy spent in a S&F cycle (recall E_{cyc} from (3)).

The above suggests that even though the nodes close to the sinks are the critical nodes, the degrading effectiveness of energy usage cannot be overlooked especially if the energy spikes are significant. In fact, one strategy to enhance the efficiency for these far away nodes is to have them store more data and use multiple paths to disperse the stored data. From the flow distribution problem perspective, this simply means balancing the flows originating from the "leaf nodes."

4.3. Sensing Effective Nodes

In Section 4.1, we consider the case where the wireless sensors in a network have about the same λ_{s}. In the case of non-uniform sensing rates, we find that higher λ_{r} may not lead to increasing total data transmitted by that sensor over its lifetime, i.e., R^*_{life} from (5), By taking a closer look at the model derived in Section 3, we derive the following corollary.

Corollary 1 *As λ_r increases and all other parameter fixed, a sensor will have*

- T^*_{life} *monotonically decreases regardless the values of other parameters, and*
- R^*_{life} *decreases if and only if* $\lambda_s/\mu > p^s/p^r$.

Proof: The proof to the corollary follows by deriving from the conditions $\frac{d\ T_{life}}{d\lambda_r} < 0$ and $\frac{d\ R_{life}}{d\lambda_r} < 0$, respectively. ■

Notice that although the sensor lifetime decreases as more flows are directed to it, the total amount of data transmitted (or forwarded) by the sensor may or may not go down as the lifetime does. In fact, the total transmission will go up as λ_r increases, if and only if it is more energy efficient to receive a bit of data from one of the neighbors rather than to sense a bit of data as the condition: $\lambda_s/\mu < p^s/p^r$ suggests. Figure 4 depicts the numerical results to show how T^*_{life} and R^*_{life} changes as λ_r increases, for the cases of $\lambda_s/\mu = 0.5 \times (p^s/p^r)$, $1.0 \times (p^s/p^r)$ and $1.5 \times (p^s/p^r)$, respectively. The results demonstrate that maximizing sensor lifetime does not necessarily mean maximizing the total data transmitted by that sensor. We argue that this is also true when applying to the entire sensor network. Also interesting from Figure 4 is that, regardless of whether sensing or receiving is more energy efficient, the total transmission approaches to the case where they are equally efficient as $\lambda_r \rightarrow \infty$[4].

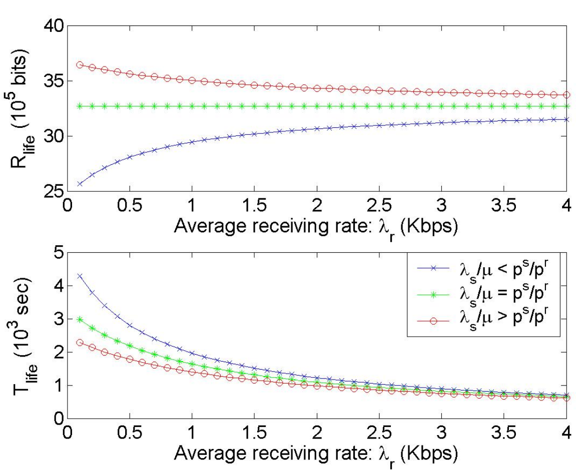

Figure 4. The changes of R^*_{life} and T^*_{life} as λ_r increases, for different cases of λ_s/μ comparing to p^s/p^r.

4 Of course λ_r can never go to infinity, since the sensor operation will not be stable if $\lambda_s + 2\lambda_r > \mu$ - recall Lemma 1.

The above study suggests that when determining the flow distribution on a wireless sensor network, it may be imperative to distinguish nodes that are more sensing effective versus those that are not. It will be wise to distribute the least flow possibile towards nodes that potentially collect much data via sensing. In other words, the sensing nodes should be allowed to focus on sensing while the other nodes forward the data.

5. Max-Retrieval Heuristics

The S&F cycle suggests that each sensor in the network should not try to transmit until its buffer is almost full, and not try to receive until its buffer is quite empty. As stated earlier, this may not be possible for all sensor nodes in general networks. Two heuristic procedures are developed to investigate the feasibility of using "online" procedures to force the wireless sensor nodes to operate in "more or less" S&F cycles, and also to determine their performance. Moreover, the analyses given in Section 4 suggest a balanced flow distribution over the network. These intuitions form the common principles for the development of our heuristics.

- (MAC) They both greedily schedule transmissions for nodes that have the most data in buffer, and schedule receptions for nodes that are in the neighborhood of the transmission nodes and have the most buffer space available to absorb data to be transmitted.
- (Routing) They both greedily direct data flows towards the sinks, by requiring the receiver of a transmission to be 1-hop closer to at least one of the sinks as compared to the transmitter.

Note that we do not suggest that the two heuristics proposed here are the best ones. They are developed and simulated to examine performance and the feasibility of S&F operations. The two heuristics are different in that one of them determines the receiver of each transmission based on the residual energy of the eligible receivers, while the other does not. We describe the two heuristics in detail below.

The first heuristic procedure takes a greedy approach that starts from the node that has the most "urgent" need to transmit, i.e., the one that has the least available buffer remaining. Once the transmitter is determined, a downstream node is designated as the receiver if its buffer usage is the smallest among the other downstream nodes of the transmitter. A node is called the downstream node of a transmitter if the receiver is one hop closer to at least one of the sinks. Once we find a transmitter-receiver pair, we can examine the network and determine the nodes that are still eligible to transmit based on the spatial reuse constraints, and go through the greedy procedure again, until no node is eligible to transmit anymore. This looping procedure greedily finds a set of transmission-receiver pairs that will be active during a time interval, where the length of the interval is to be determined.

The determination of the length of the time interval needs to be such that no buffer will overflow due to sensing and/or receiving. To prevent the heuristic from entering a loop of finding small time intervals, an α ($0 < \alpha < 1$) parameter is used to restrict the set of eligible nodes that can be selected to transmit. That is, node i will be eligible to transmit only if the buffer usage is larger than αb_i, where b_i is the buffer size of sensor i. If none of the nodes in the network are eligible to transmit in a given time interval, the heuristic will find the time interval such that at the end of the interval, at least one node in the network will fill its buffer to almost full. By "almost full", we mean that the node i will fill its buffer to $b_i + \beta(b_i - d_i)$, where $0 < \beta < 1$ and d_i is the buffer usage of sensor i at the beginning of the time interval. This criterion will be used for determining the time interval to ensure no buffer overflow, while preventing multiple neighboring nodes from becoming full at the end of the time interval, which will then not be able to transmit at the same time due to spatial reuse constraints. Once the time interval and the transmission-receiver pairs for this interval are determined, the heuristic will move on to the next time interval based on the updated sensor status. The above ideas build the foundation of our first heuristic, Greedy-Buffer(α, β) (GB) algorithm, as shown in Figure 5.

One problem arises when using the heuristic GB. Choosing the receivers based on the buffer usage alone balances the data flow to downstream nodes, but does not balance the energy spent by these downstream nodes. In fact, our experience with GB shows that over time every node in the network will transmit its data equally to its downstream neighbors. This equal distribution may result in a bottleneck node that has its energy drained the quickest, while there are other available nodes that could have helped to forward a portion of the data that was passed to the bottleneck node. A second heuristic Greedy-Energy(α, β, γ) (GE), therefore, is developed and shown in the bottom of Figure 5. The heuristic GE balances the use of energy for the downstream nodes of a transmitter, by determining the receiver as the one that has the largest residual energy and has its buffer usage $d_i < \gamma b_i$. If no downstream node satisfies the buffer usage constraint, the heuristic then chooses the one that has the largest residual energy to be the receiver.

We examine the two heuristics by simulating them over 30 randomly generated networks; each has 15 sensor nodes and 5 sinks. All nodes in the network are guaranteed to connect to at least one sink, via either direct connection or through multiple hops. We consider a homogeneous case where all nodes have c=10 Kbps, b=30 Kbits, $(p^s,\ p^r,\ p^t) = (0.001,\ 0.01,\ 0.01)$ (W), and $(e^{sr},\ e^{rt}) = (0.001,\ 0.001)$ (J). For each topology, six different offered loads were applied, with the average sensing rates to individual sensors being 100 bps, 200 bps, 500 bps, 800 bps, 1 Kbps, and 1.3 Kbps, respectively. Simulation results exhibiting the total data retrieval by using the two heuristics, are shown in Figure 6. The total network retrieval is the total amount of data received at the sinks before the first sensor dies in the network.

Greedy-Buffer(α, β):
while (allNodeHasEnergy)
    eligibleTxNodes = N;
    while (eligibleTxNodes_not_empty)
        For ($i \in$ eligibleTxNodes)
            $s_i = (b_i - d_i) / \lambda_i$;
            if ($s_i < s_{\min}$)
                nextToTx $= i$; $s_{\min} = s_i$;
        For ($i \in N_{\text{nextToTx}} \cap N_{\text{hop}_i - 1}$)
            if ($d_i < d_{\min}$)
                nextToRc $= i$; $d_{\min} = d_i$;
        update_eligibleTxNodes(nextToTx,nextToRc,α);
        For ($i \in N$)
            if (timeToFillBuf$_i(\beta) < T_k$)
                T_k =timeToFillBuf;
    update_network_status;

Greedy Energy (α, β, γ):
while (allNodeHasEnergy)
    eligibleTxNodes = N;
    while (eligibleTxNodes_not_empty)
        For ($i \in$ eligibleTxNodes)
            $s_i = (b_i - d_i) / \lambda_i$;
            if ($s_i < s_{\min}$)
                nextToTx $= i$; $s_{\min} = s_i$;
        For ($i \in N_{\text{nextToTx}} \cap N_{\text{hop}_i - 1}$)
            if ($e_i > e_{\max,1}$)
                nextToRc $= i$; $e_{\max,1} = e_i$;
            if ($e_i > e_{\max,2}$ && $d_i < \gamma b_i$)
                nextToRc $= i$; $e_{\max,2} = e_i$;
        update_eligibleTxNodes(nextToTx,nextToRc,α);
        For ($i \in N$)
            if (timeToFillBuf$_i(\beta) < T_k$)
                T_k =timeToFillBuf;
    update_network_status;

Figure 5. The heuristics for the MDR problem.

Also shown in the two figures are theoretical estimates of the total data retrieval based on the analysis described in Section 3. More specifically, we compute the network total retrieval R_{tot} based on the following formula.

$$R_{\text{net}} = \sum_{i \in N(S)} \left(\frac{\min_{j \in N} T_{\text{life},j}}{T_{\text{cyc},i}} \cdot R_{\text{cyc},i} \right). \qquad (6)$$

Note that in deriving $T_{\text{cyc},i}$ and $T_{\text{life},i}$, one needs to know the average receiving rate for each sensor. We estimate the average receiving rates by assuming equal distribution of data flows among shortest paths (i.e., over the nodes that are closer to the sinks). This theoretical estimation may be considered as the ideal version of the GB algorithm.

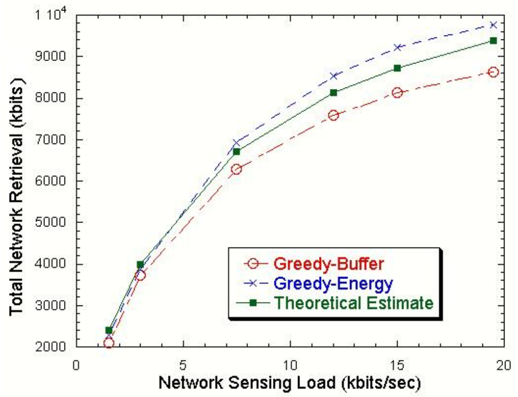

Figure 6. The total data retrieval (averaged over 30 random topologies) as the offered load increases, using both heuristics and based on the theoretical estimate.

Notice from Figure 6 that the GB algorithm performs not too far from the theoretical estimate, especially in the light load regime. This suggests that the greedy MAC approach, in determining the transmitter-receiver pairs based on the buffer content, performs well in mimicking the ideal S&F operations. Second, with GE outperforming the theoretical estimate, it implies that balancing flows based on the residual energy achieves a higher volume of data retrieved as compared to balancing flows over the available shortest paths. Note that the good MAC and routing policies are actually integrated, since GE in fact uses the buffer content and the residual energy together to infer both the transmission schedule and the next hop to forward data.

The accurate prediction by the theoretical estimate is somewhat surprising but reasonable. In fact, a careful examination of the sensor operations tells that by using the two heuristics, most nodes exhibit periodical S&F cycles similar to that suggested in Section 3. Note that the networks are simulated without using actual network protocols. Consequently, there are no collision, no retransmission and no control overhead. Nevertheless, our simulation results validate the feasibility of S&F operations by using online policies, and show the capability of achieving performance close to the ideal case, where all nodes are assumed to be able to transmit and receive as needed.

6. Concluding Remarks

It is a general belief that the use of multi-mode wireless sensors is the key to energy efficient networked sensing. A formal model, however, is greatly needed to investigate the optimal routing and scheduling of multi-mode sensor operations to achieve the most out of a sensor network given individual sensor resource constraints. We have developed a joint MDR problem that maximizes the total data transmitted to the sinks subject to the spatial reuse constraints and various multi-mode wireless sensor resource constraints. In particular, our model truly reflects the penalty for switching between operational modes as well as the benefit to buffer sensed data. Though complex, the formulation allows us to observe that periodical store-and-forward leads to good performance.

Closed form equations have been developed for the ideal S&F cycle. The analytical model developed, though simple, provides not only new avenues in solving the complex joint optimization problem, but also theoretical foundation to practical online policies. Variants of flow distribution problems based on our S&F models are under investigation to examine their closeness to the MDR problem. Meanwhile, we are developing cross-layered protocols based on the proposed heuristic procedures to perform data forwarding and sensor operational mode scheduling. The key to our protocol design is for each sensor in the network to be able to gather (or overhear) critical information that estimates the buffer usage and the residual energy of the neighbors, with minimal, if not zero control overhead. Our ultimate goal is to have wireless sensors to autonomously schedule their operation schedule and forwarding direction so as to achieve close to the maximum achievable retrieval of data given individual sensor resource constraints.

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