Localized Power-Aware Routing in Linear Wireless Sensor Networks

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ABSTRACT

Energy-efficency is a key concern when designing protocols for wireless sensor networks (WSN). This is of particular importance in commercial applications where demonstrable return on investment is a crucial factor. One such commercial application that motivated this work is telemetry and control for freight railroad trains. Since a railroad train has a global linear structure by nature, we consider in this paper linear WSNs as sensor networks having, roughly, a linear topology. Aiming at such networks, we introduce two routing schemes that efficiently utilize energy: Minimum Energy Relay Routing (MERR) and Adaptive MERR (AMERR). We derive a theoretical lower bound on the optimal power consumption of routing in a linear WSN, where we assume a Poisson model for the distribution of nodes along a linear path. We evaluate the efficiency of our protocols with respect to the theoretical optimal lower bound and with respect to other well-known protocols. AMERR achieves optimal performance for practical deployment settings, while MERR rapidly approaches optimal performance as sensors are more densely deployed. Compared to other protocols, we show that MERR and AMERR are less complex and have better scalability. We also postulate how both protocols might be generalized to a two-dimensional WSN.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Wireless Communication*

General Terms

Algorithms, Design, Performance, Theory

Keywords

Wireless Sensor Network, Linear Topology, Localized Protocol, Routing, Energy Efficiency

1. INTRODUCTION

Several applications have been proposed for wireless sensor networks (WSN). Some of these are accompanied by field investigation and test; interesting observations have been made, and encouraging results have been obtained. Some examples are habitat monitoring [20], active volcano sensing [33], structural health monitoring [5], and geolocation in underground mines [22]. These applications are, however, by and large, limited to the public sector. Today, real world, commercial applications are beginning to emerge, particularly in private sector business. Unlike the public sector, demonstrable return on investment is paramount for the viability of private sector WSN applications. Consequently, designing WSNs for the private sector often requires optimizations that are overlooked for public sector applications. In this paper, we consider one such optimization: energy-aware routing over a *linear* WSN.

We consider a linear WSN to be a sensor network having, roughly, a linear topology. That is, though the sensors nodes are not deployed exactly on a straight line, they can be considered as such. Data propagation is assumed to be unidirectional. Networks with such topology appear in various applications, including structural health monitoring [5] and pipeline monitoring [28]. The application that motivated this work is, however, telemetry and control for freight railroad trains. Using sensor networks to provide more timely information, the goal of this application is to attain greater visibility of the rolling assets and cargo. With greater visibility into the health and status of their trains, railroad companies improve safety and resource utilization while reducing liability and maintenance costs. A typical concern in freight railroads is derailments. This is of particular concern with transporting hazardous materials. High cost in liability (personal, property, and environment) as well as lost revenue from downtime are usually associated with derailments. A primary cause of derailments is component failure such as a cracked wheel. Through sensor-based failure prediction of a train's components, it is possible to substantially reduce the number of derailments. Moreover, in the case of component failure, onboard event processing can improve response time to failure conditions, thereby reducing the failure's impact. The network and application architecture of sensor-based freight railroad train monitoring is shown in Figure 1. This is a promising commercial application space for sensor networks with many challenges; though, the one challenge we focus on in this paper is optimizing energy usage for in-field longevity.

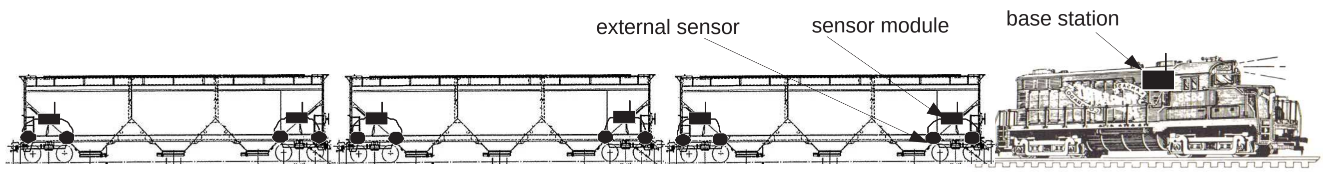


Figure 1: A small segment of a freight railroad train is depicted. Sensor modules with external sensors are deployed near or on the wheels where failures most commonly occur. For example, acoustic sensors might be used to detect cracked or flat wheels, while a thermocouple might be used to detect overheated wheel bearings. The sensor modules relay sensor data and alert events to a base station, which is deployed on the locomotive.

A freight railroad train can have up to 150 cars, where the average car length is about 60 feet (about 18 meters). This equates to a maximum train length of more than 1.7 miles (about 2.7 kilometers). In comparison to most WSN applications, this is a substantial communication distance to cover. Today, there are more than 1.4 million railroad cars in North America alone, most of which are without onboard power. To be viable, the maintenance cost of the WSN infrastructure should not add appreciably to the existing maintenance costs. Railroad cars should not be hauled in just to service the WSN infrastructure, but it is plausible to service the WSN infrastructure during regular maintenance of a railroad car. Thus, each sensor node's energy lifetime must be at least as long as the maintenance cycle of a car, which can exceed five years. These requirements, several years of longevity and long communication distances, motivate our in-depth study of localized and energy-efficient routing protocols for linear WSNs.

In this paper, we derive a lower bound on the optimal power consumption of routing in a linear WSN, where we assume a Poisson model for the distribution of sensors along a linear path. We present two new localized power-aware routing protocols: (1) Minimum Energy Relay Routing (MERR) and (2) Adaptive MERR (AMERR). We evaluate MERR and AMERR by comparing their power consumption to other well-known protocols and to the optimal lower bound. For Poisson rates of 0.10 or greater, AMERR achieves optimal performance, while MERR rapidly approaches optimal performance as the Poisson rate increases. Compared to other protocols, we show that MERR and AMERR are less complex and have better scalability. These findings are based on simulation results complemented by theoretical analysis. We also postulate how MERR and AMERR might be generalized to a two-dimensional WSN.

We organize the paper as follows. Section 2 summarizes related work, including a review of existing localized power-aware routing algorithms used for comparison with our own algorithms. Section 3 outlines the system model which we use throughout the discussion. Section 4 presents the optimal routing analysis, where we derive a lower bound on the optimal power consumption of routing in linear WSNs. In Section 5, we present two new localized power-aware routing protocols for linear WSNs: MERR and AMERR. There we also discuss how these protocols might be adapted toward general two-dimensional sensor networks. We evaluate our algorithms in Section 6 based on stochastic analyses as well as simulation results. Lastly, we offer some concluding remarks and directions for future work in Section 7.

2. RELATED WORK

Power-aware algorithms for routing in WSNs have received considerable attention over the past few years. A distributed position-based algorithm to form topologies containing a minimum total energy route between any pair of connected nodes is proposed in [26]. Based on this initial work, a computationally simpler protocol with better performance is described in [18]. Similar topology control algorithms based on discretization of the coverage region of a node into cones are proposed in [19, 32]. The idea is to select appropriate transmitter power levels to guarantee network connectivity while at the same time transmission energy is saved.

Putting a node into sleep mode whenever its active collaboration in the current network task is not required is another way to save energy. The geographical adaptive fidelity (GAF) algorithm [34] conserves energy by turning off nodes that are equivalent from a routing perspective, thereby keeping a constant level of routing fidelity. An improvement of GAF based on a relationship between optimal transmission range and traffic is described [9]. In Span [4], the decision whether a node should be awake or sleep is made depending on how many of its neighbors will get benefit and how much remaining energy it has. The sparse topology and energy management (STEM) protocol [27] puts nodes aggressively into sleep mode and only wakes them up when they are needed to forward data. Data fusion is a technique that can be used to reduce the amount of redundant information prevalent in dense sensor networks. By combining data with equal semantics, unnecessary power consumption due to transmission and processing of duplicate data is prevented. Two prominent routing protocols that use upper layer information for data fusion as well as making routing decisions are Directed Diffusion [13] and SPIN [16]. Application-specific fusion enables even more sophisticated data and node management functionalities inside WSNs [12]. Both sleep scheduling and data fusion are desirable functionalities which may complement energy-efficient MAC and routing protocols.

The scalability problem of WSN protocols is discussed in [7]. The authors argue that *localized* algorithms, where a node exchanges information only with its direct neighbors, provide for good scalability. Our proposed routing algorithms are localized in the sense that each node decides on the next hop based only on the position of itself, of its neighbors, and possibly of the destination node. Other techniques developed to cope with scalability in large sensor networks are to introduce heterogeneity [6], hierarchy [23,24, 35], clustering [10,12,36], and location-awareness [15,30,34].

Our work is primarily inspired by the work of Bhardwaj, Garnett, and Chandrakasan [3] and Stojmenovic and Lin [30]. Bhardwaj et al. [3] derive upper bounds on the network lifetime of information harvest sensor networks that convey probabilistic data from a point, a line, or an area source. Assuming sensor nodes being capable of adjusting their transmission output power, these bounds are based on the observation that there exists a certain optimal transmission range if minimum total energy is the desired objective. Similar results are described by Stojmenovic and Lin [30]. They derive optimality criteria of power-adjusted transmissions and present a position-based localized routing algorithm. This algorithm as well as two others proposed by Kuruvila, Nayak, and Stojmenovic [17] is a well-known localized power-aware routing algorithm. We review these algorithms briefly in the following and compare them with our own protocols in Section 6. An overview of position-based routing protocols is given in [29]; general surveys of routing protocols for sensor networks can be found in [1, 2].

Stojmenovic and Lin [30] propose the nearest closer (NC) algorithm, where a node, currently holding the message, forwards it to the nearest neighbor. Minimum transmission energy (MTE) routing of Heinzelman, Chandrakasan, and Balakrishnan [12] does the same, although the next hop is actually chosen such that the transmit amplifier energy is minimized. Both algorithms, referred to as the *NC/MTE* method in our evaluation, consider only nodes closer to the destination than the current node. Unlike NC/MTE, the localized greedy scheme of Finn [8] as well as the most forward within radius (MFR) method of Takagi and Kleinrock [31] select the neighbor that is closest to the destination. With this strategy, maximal progress is made toward the base station within a single hop, thereby minimizing the total hop count. We refer to both schemes as *Greedy/MFR*.

NC/MTE and Greedy/MFR consider only the pure distances to neighbors when deciding on the next hop. Stojmenovic and Lin [30] motivate a more sophisticated power metric. In their algorithm, a source node S selects neighbor A, where A must be closer to the destination D than S, that minimizes the sum of (1) the power needed to transmit from S to A and (2) the estimated power needed on the remaining path from A to D. If the destination D is a neighbor of S, the power needed for direct transmission to D is also considered. We term this algorithm *Estimation* for the remainder of this paper.

Kuruvila et al. [17] introduce the notion of *proportional progress*, which they define as the power used to make a portion of progress toward the destination. They propose two different metrics to quantify proportional progress. The first metric relies on the distance from source S to destination D, d_{SD}, and on the distance from neighbor A of S to destination D, d_{AD}. The progress made when S forwards to A is defined as the difference of these two distances, $d_{SD} - d_{AD}$, and the proportional progress is defined as the ratio of the power needed to transmit from S to A and the associated progress. The neighbor with minimal proportional progress is selected. We refer to this algorithm as *Progress*. The second metric relies on the vectors SA and SD. The progress made when S forwards to A is defined as the dot product of these two vectors. The proportional progress is adapted accordingly. As in the first metric, the neighbor with minimal proportional progress is selected. We refer to this variant as *Progress Vector* in our evaluation.

3. SYSTEM MODEL

We now outline the basic network and energy model that we use throughout this paper.

Network Model: The topology of a WSN is determined by the positions of the sensor devices that belong to the network. In this work, we consider sensor networks that are composed of n sensors and one base station arranged along a line (see Figure 2). Each sensor node has a unique ID, starting with node 1 right of the base station.

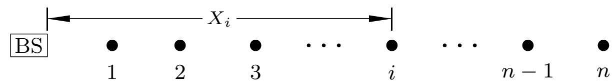


Figure 2: A linear network of n sensors and one base station.

The actual sensor positions in a real deployment depend on various factors such as structural conditions and application requirements. We choose a *one-dimensional homogeneous Poisson process* to model the distribution of sensors in order to capture a wide range of different network configurations. The points of the Poisson process represent a random sequence of sensor nodes distributed on a straight line. Because a Poisson model is, in a sense, the most random way in which to describe any particular phenomenon [14], our results obtained by using this model are general enough to be valid for many different application scenarios. As shown in Figure 2, X_i denotes the random distance between node i and the base station, whereas node i is the i-th point of the Poisson process. A homogeneous Poisson process is characterized by its constant *rate* λ. In our domain, λ is a measure of node density (number of nodes per length unit), and $1/\lambda$ corresponds to the mean distance between adjacent nodes. We refer to this model as the *Poisson Node Model*.

Energy Model: Communication consumes significant power in WSNs. We therefore focus on the communication-related power consumption of the sensor nodes and adopt a widely-used energy model (see, for example, [3, 11, 12]). The base station is assumed to have unlimited energy supply. For a sensor to transmit a bit-stream of rate r over a distance d, the transmitter power $P_{tx}(r, d)$ is

$$P_{tx}(r, d) \;=\; r(\alpha_{tx} + \epsilon\, d^{\gamma}), \tag{1}$$

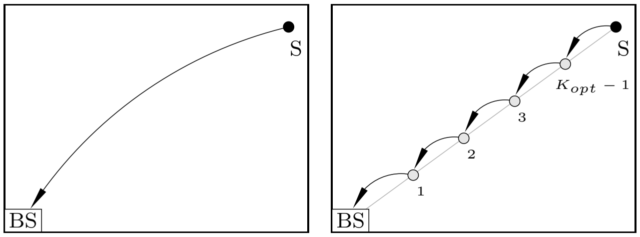
where α_{tx} is the energy per bit consumed in the transmitter circuit, and ϵ accounts for the energy dissipated in the transmit amplifier. The *path loss exponent* γ typically ranges between 2 and 6; it is closer to 2 if there is a perfect line-of-sight between transmitter and receiver and can go up to 6 in dense urban areas [25]. The power $P_{rx}(r)$ needed to receive a bit-stream of rate r is

$$P_{rx}(r) \;=\; r\alpha_{rx}, \tag{2}$$

where α_{rx} is the energy per bit consumed by the receiver circuit. Hence, for a sensor to receive a bit-stream of rate r and to forward it a distance d onward, the power consumption is given by

$$\begin{aligned} P_{relay}(r, d) \;&=\; r(\alpha_{rx} + \alpha_{tx} + \epsilon\, d^{\gamma}) \\ &\equiv\; r(\alpha + \epsilon\, d^{\gamma}). \end{aligned} \tag{3}$$

As P_{tx}, P_{rx}, and P_{relay} scale linearly with r, we omit this term in the following and implicitly assume $r = 1$ bit/s.



(a) Direct transmission. (b) Retransmission.

Figure 3: Minimum energy path from S to BS.

4. OPTIMAL ROUTING

In this section, we study routing paths that are optimal with regard to total power consumption and derive a corresponding theoretical lower bound based on the Poisson Node Model.

4.1 Minimum Energy Paths

Suppose that a sensor S is located at distance D from the base station BS, as shown in Figure 3, and that S wants to deliver some data to BS. The goal is to minimize the power needed on the entire path from S to BS. According to [30], S should transmit directly to BS if $D \leq (\alpha/(\epsilon(1-2^{1-\gamma})))^{1/\gamma}$ (see Figure 3(a)). Otherwise, it is best to select $(K_{opt}-1)$ equally spaced, intermediate nodes for retransmission (see Figure 3(b)). K_{opt} is the optimal number of hops which is

$$K_{opt} \;=\; \left\lfloor \frac{D}{d_{char}} \right\rfloor \text{ or } \left\lceil \frac{D}{d_{char}} \right\rceil, \qquad (4)$$

where d_{char} is the *characteristic distance* [3] given by

$$d_{char} \;=\; \sqrt[\gamma]{\frac{\alpha}{\epsilon(\gamma-1)}}. \qquad (5)$$

The optimal number of hops K_{opt} in (4) depends on the distance D between S and BS as well as on the characteristic distance d_{char}. D can change over time if the sensors and/or the base station are mobile. The characteristic distance, though, is a constant for all nodes in the network. This is true as long as the following two conditions hold. First, all sensor devices are equipped with the same radio, yielding to equal radio characteristics (α, ϵ) at all nodes. Second, the conditions of the propagation environment are reasonably stable, which makes the assumption of a constant path loss exponent (γ) plausible. The following theorem states which of the two alternatives in (4) yields in fact the optimal number of hops. Stojmenovic and Lin [30] as well as Bhardwaj et al. [3] did not provide a proper solution to this problem.

Theorem 1. *Let $m = \lfloor D/d_{char} \rfloor$ and $\delta = D/d_{char} - m$. The choice $K_{opt} = \lfloor D/d_{char} \rfloor$ is optimal if*

$$\delta \;\leq\; \sqrt{m^2+m} - m, \qquad (6)$$

for $\gamma = 2$, and

$$\delta \;\leq\; \sqrt[4]{\frac{3m^3(m+1)^3}{3m^2+3m+1}} - m, \qquad (7)$$

for $\gamma = 4$, respectively. Otherwise, $K_{opt} = \lceil D/d_{char} \rceil$ is preferable in each case.

Algorithm 1 Computation of optimal number of hops K_{opt}

Input: D, d_{char}, γ
Output: K_{opt}
1: Let $m := \lfloor D/d_{char} \rfloor$ and $\delta := D/d_{char} - m$
2: $t := 0$ (* initialize auxiliary variable t *)
3: **if** $\gamma = 2$ **then**
4: $\quad t := \sqrt{m^2+m} - m$
5: **else** (* $\gamma = 4$ *)
6: $\quad t := \sqrt[4]{\frac{3m^3(m+1)^3}{3m^2+3m+1}} - m$
7: **end if**
8: $K_{opt} := 0$ (* initialize K_{opt} *)
9: **if** $\delta \leq t$ **then**
10: $\quad K_{opt} := m$
11: **else** (* $\delta > t$ *)
12: $\quad K_{opt} := m+1$
13: **end if**
14: **return** K_{opt}

Proof. Suppose there are $(K_{opt}-1)$ equidistant nodes between S and BS. The total power needed to relay a bitstream with unit rate via these nodes is

$$P_{total}(D) \;=\; -\alpha_{rx} + K_{opt}\, P_{relay}\left(\frac{D}{K_{opt}}\right), \qquad (8)$$

where P_{relay} is given by (3). The decision whether $\lfloor D/d_{char} \rfloor$ or $\lceil D/d_{char} \rceil$ is the best choice for K_{opt} can be made by computing the power rates for both alternatives via (8) and subsequently comparing them with each other. We set $m = \lfloor D/d_{char} \rfloor$ and $\delta = D/d_{char} - m$ to eliminate the floor and ceiling function. With this, the two alternatives simplify to $\lfloor D/d_{char} \rfloor = m$ and $\lceil D/d_{char} \rceil = m+1$, and D can be expressed as $D = (m+\delta)\, d_{char}$. Hence, the power P^m_{total} needed with $K_{opt} = m$ hops is

$$P^m_{totol}(D) \;=\; -\alpha_{rx} + m\, P_{relay}\left(\frac{(m+\delta)\, d_{char}}{m}\right), \qquad (9)$$

and the power P^{m+1}_{total} needed with $K_{opt} = m+1$ hops is

$$P^{m+1}_{total}(D) \;=\; -\alpha_{rx} + (m+1)\, P_{relay}\left(\frac{(m+\delta)\, d_{char}}{m+1}\right). \qquad (10)$$

By solving the inequality

$$P^m_{total}(D) \;>\; P^{m+1}_{total}(D) \qquad (11)$$

with respect to δ for $\gamma = 2$ and $\gamma = 4$, we obtain (6) and (7), respectively. $\square$

Algorithm 1 demonstrates the application of Theorem 1 to compute the optimal number of hops. It takes as input the distance D of a sensor to the base station, the characteristic distance d_{char}, and the path loss exponent γ. In case sensors and base station are static, all these input parameters are constant. If either sensors or base station are mobile, D is the only variable input parameter. Let us walk through Algorithm 1 using the following sample parameters: $D = 122$ m, $d_{char} = 50$ m, and $\gamma = 4$. For these values, we have $m = 2$ and $\delta = 0.44$ (line 1). Because $\gamma = 4$, we get $t = 0.42$ in line 6. Thus, $\delta > t$, and we get $K_{opt} = 3$ (line 12). The algorithm returns 3 (instead of 2) as the optimal number of hops. Consequently, transmission power will be minimal if 2 ($= K_{opt} - 1$) equidistant sensor nodes are selected for relaying data from S to BS. Algorithm 1 can be executed by a sensor node either in an initial setup phase or whenever the distance to the base station has changed. As we will see in Section 5.2, the ability of a node to determine the optimal number of hops is essential to further reduce the power consumption of localized routing protocols.

Stojmenovic and Lin [30] propose to use D/d_{char}, rounded to the closest integer, as the most suitable number of hops. In general, this simple approach does not yield the optimum. Using the sample values from above, $D/d_{char} = 2.44$ rounded to the closest integer amounts to 2, which is not the actual optimal number of hops. We therefore believe that our optimal routing analysis provides a more precise characterization of minimum energy paths compared to previous work.

4.2 Lower Bound on Power Consumption

We now derive a lower bound on the optimal power consumption of routing for the Poisson Node Model. In this model, the n-th sensor node is located at random distance X_n from the base station. According to the previous section, this distance should be covered by making K_{opt} hops of equal length in order to minimize overall power consumption. In theory, we would therefore place $(K_{opt} - 1)$ relays equally on the connecting line between sensor n and the base station. The power needed for relaying data along this optimal path is the lower bound with regard to node n in the Poisson Node Model. We compare our new routing protocols as well as existing approaches with this bound in Section 6.

THEOREM 2. *For the Poisson Node Model, the minimum expected power consumption for relaying a bit-stream with unit rate from node n to the base station is*

$$\mathbb{E}[P_{OPT}(X_n)] \; = \; -\alpha_{rx} + K_{opt}\left[\alpha + \epsilon\left(\frac{n}{\lambda K_{opt}}\right)^{\gamma}\right], \quad (12)$$

where X_n is the distance of node n to the base station and K_{opt} is the optimal number of hops (given by Theorem 1).

PROOF. The distance of node n to the base station is $X_n = n/\lambda$. Hence, each hop is of length $Y = n/(\lambda K_{opt})$, and the power consumed at each hop is given by

$$\mathbb{E}[P_{relay}(Y)] \; = \; \alpha + \epsilon\left(\frac{n}{\lambda K_{opt}}\right)^{\gamma}. \quad (13)$$

Then, the expectation of power for all K_{opt} hops is

$$\begin{aligned}\mathbb{E}[P_{OPT}(X_n)] \; &= \; \mathbb{E}[-\alpha_{rx} + \textstyle\sum_{i=1}^{K_{opt}} P_{relay}(Y)] \\ &= \; -\alpha_{rx} + K_{opt}\, \mathbb{E}[P_{relay}(Y)], \quad (14)\end{aligned}$$

where $\mathbb{E}[P_{relay}(Y)]$ is given by (13). □

5. NEW LOCALIZED POWER-AWARE ROUTING PROTOCOLS

In the previous section, we discussed the theoretical case that a certain optimal number of relays can be placed at desired positions to set up a minimum energy path. In a real linear WSN, however, where sensors may be deployed at arbitrary positions, such an optimal path is very unlikely to exist. The best we can do is to select appropriate existing nodes for retransmission in order to approximate the optimal case. This approximation should be made in a localized manner, that is, each sensor node in the network decides autonomously on the next hop solely based on the position of itself, of its neighbors, and possibly of the destination node. Hence, sensor nodes only need to communicate with sensors within some regional neighborhood. Such localized operation allows algorithms to scale well with increase in network size and to be robust to network partitions and node failures [7]. Moreover, the lower communication overhead compared to centralized algorithms reduces power consumption considerably.

We now present two new localized power-aware routing protocols for linear WSNs: MERR and AMERR. In addition to the benefits of localization, both protocols try to approximate minimum energy paths. The difference between MERR and AMERR is the amount of information assumed to be available to a sensor node when selecting the next hop. While MERR only assumes that a sensor node is aware of the distances to its downstream[1] neighbors, AMERR assumes also that a sensor knows the distance to the base station. This additional knowledge allows AMERR to make better routing decision than MERR at the cost of a lower degree of locality. Please note that we outlined the basic concept of MERR before in [37]. Compared to the former paper, we now specify the protocol in more detail, derive the expected power consumption of MERR for the Poisson Node Model, present AMERR as an advancement of MERR, and compare both approaches with other well-known algorithms described in the literature.

5.1 MERR: Minimum Energy Relay Routing

The characteristic distance can be considered as an optimal forwarding distance, that is, the distance that a node should transmit its data onward in order to minimize the power consumed on the entire path to the base station. With this observation in mind, we can describe the basic idea of MERR as follows. In the trivial case that the base station BS is a neighbor of sensor S and the distance D between them is shorter than $(\alpha/(\epsilon(1 - 2^{1-\gamma})))^{1/\gamma}$, S transmits directly to BS. If D is longer than this threshold, S selects node A among its downstream neighbors whose distance is *closest to the characteristic distance*. Upon making the decision on the next hop A, sensor S adjusts its radio output power to the lowest possible level such that the signal can just be received by node A. During normal operation, S forwards its own data as well as data received from other upstream sensors to A. Whenever there is a change in the topology such that the distance between S and A is affected, or another sensor gets closer to the characteristic distance than A, sensor S starts the search for its best next hop anew.

Algorithm 2 shows the selection of the next hop in MERR. It takes as input the set of downstream neighbors of sensor S and the characteristic distance. Starting with some neighbor N_1 (line 1), the deviation of the distance between S and N_1 from the characteristic distance is computed (line 2). Then, all neighbors are successively examined in order to find the neighbor with minimum deviation (line 3 to 8). Sensor S forwards its data to the neighbor returned by Algorithm 2. Figure 4 illustrates how a complete path is established with MERR. By running Algorithm 2, node 5 selected node 4 as next hop, node 4 selected node 2, and node 2 decided to transmit directly to the base station BS. Hence, data from sensor 5 is relayed via intermediate nodes 4 and 2 to BS. The following theorem states how much power is consumed on such a routing path for the Poisson Node Model.

[1]Downstream means toward the base station.

Algorithm 2 Selection of next hop in MERR

Input: neighbors $N_1, \ldots, N_k$ of S, d_{char}
Output: next hop node A

```
A := N_1                                   (* initialize A *)
Δ := |distance(S, N_1) − d_char|           (* deviation *)
for i := 2, ..., k do
    Δ' := |distance(S, N_i) − d_char|      (* deviation *)
    if Δ' < Δ then
        A := N_i and Δ := Δ'
    end if
end for
return A
```

THEOREM 3. *For the Poisson Node Model, the expected power consumption for relaying a bit-stream with unit rate from node n to the base station is*

$$\mathbb{E}[P_{MERR}(X_n)] \;=\; -\alpha_{rx} + \frac{n}{\lambda d_{char}}\,\mathbb{E}[P_{relay}(Y)], \qquad (15)$$

with

$$\mathbb{E}[P_{relay}(Y)] \;=\; \alpha + \frac{\epsilon\omega^n}{\lambda^\gamma\Gamma(n)}\int_0^\infty \frac{\Gamma(z+\gamma)}{\Gamma(z)}\,z^{-(n+1)}e^{\omega z^{-1}}\mathrm{d}z, \qquad (16)$$

where X_n is the distance of node n to the base station, Y is the random distance between successive relays, z is the number of hops between successive relays, and $\omega = n\lambda d_{char}$.

PROOF. The distance of node n to the base station is $X_n = n/\lambda$. The MERR protocol attempts to divide this distance into intervals of equal length, where the length of each interval corresponds approximately to d_{char}. Let now random variable $Z = nd_{char}/X_n$ denote the number of hops within a single interval. Random variable Z has inverse gamma distribution with probability density given by

$$f_Z(z) \;=\; \frac{\omega^n}{\Gamma(n)}\,z^{-(n+1)}\,e^{-\omega z^{-1}}, \qquad (17)$$

where $\omega = n\lambda d_{char}$. Each interval is enclosed by two nodes that are responsible for relaying data from node n toward the base station. The conditional expectation of power consumed at a relay is

$$\mathbb{E}[P_{relay}(Y)|Z=z] \;=\; \alpha + \frac{\Gamma(z+\gamma)\,\epsilon}{\Gamma(z)\,\lambda^\gamma}. \qquad (18)$$

By weighing (18) with (17),

$$\mathbb{E}[P_{relay}(Y)] \;=\; \int_0^\infty \mathbb{E}[P_{relay}(Y)|Z=z]\cdot f_Z(z)\,\mathrm{d}z, \qquad (19)$$

we get the expected power consumption at a relay (16). Next, let random variable K be the number of hops needed to reach the base station via all relays. The expectation of K is $\mathbb{E}[K] = n/(\lambda d_{char})$, and the expected power consumption for making these K hops is

$$\begin{aligned}\mathbb{E}[P_{MERR}(X_n)] \;&=\; \mathbb{E}[-\alpha_{rx} + \textstyle\sum_{i=1}^{K} P_{relay}(Y)] \\ &=\; -\alpha_{rx} + \mathbb{E}[K]\,\mathbb{E}[P_{relay}(Y)], \qquad (20)\end{aligned}$$

which yields (15). □

Theorem 3 provides a general solution for arbitrary values of the path loss exponent γ. In real world deployments, γ is either determined by intensive on-site measurements or some empirical value is chosen. For instance, in the ideal case that sensor nodes enjoy a direct line-of-sight with their neighbors, a path loss exponent of $\gamma = 2$ is plausible. Recent field studies (see, for example, [21]) suggest $\gamma = 4$ as a more realistic assumption. For these two integer values, we derived from (16) exact but rather complex expressions, but we skip them here in favor of a clear presentation.

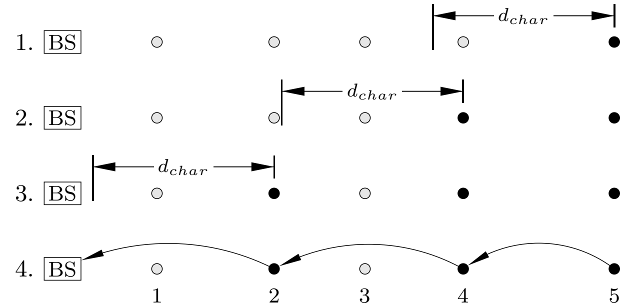
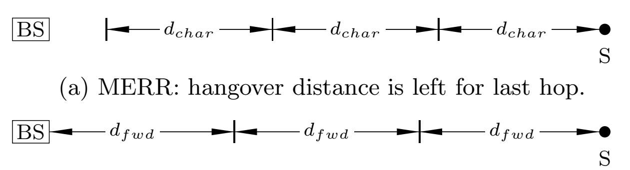


Figure 4: Establishing a routing path with MERR.

5.2 AMERR: Adaptive Minimum Energy Relay Routing

In MERR, a sensor S forwards data to that downstream neighbor whose distance is closest to the characteristic distance. In doing so, S basically assumes that the distance to the base station BS is an integral multiple of the characteristic distance. This leads virtually always to a hangover distance, as shown in Figure 5(a). The length of the last hop to BS is different from the length of the previous hops, therefore violating the property of equal hop lengths in minimum energy paths. This shortcoming can be fixed as follows, provided that S is aware of the distances D to the base station. Sensor S computes via Algorithm 1 the optimal number of hops K_{opt} that should be made along the path to BS. Then, the distance D between S and BS can be divided into intervals of length $d_{fwd} = D/K_{opt}$, as shown in Figure 5(b). In this way, hangover distances are avoided, and all hops are of equal length. We refer to d_{fwd} as the *adapted forwarding distance* because it depends on the respective distance of a sensor to the base station; its value is *adapted* for each sensor on an individual basis.



(a) MERR: hangover distance is left for last hop.

(b) AMERR: all hops are of equal length.

Figure 5: Difference between MERR and AMERR.

The basic idea of AMERR is to use the adapted forwarding distance when selecting the next hop. A sensor selects that node among its neighbors whose distance is *closest to the adapted forwarding distance.* This is the only difference to MERR, where the selection is made based on the constant characteristic distance. Algorithm 3 demonstrates the selection of the next hop in AMERR. Compared to Algorithm 2, it takes the distance D of a sensor S to the base station as an additional input parameter. First, the optimal number of

Algorithm 3 Selection of next hop in AMERR

Input: neighbors $N_1, \ldots, N_k$ of S, D, d_{char}
Output: next hop node A

1: Compute K_{opt} using Algorithm 1
2: $d_{fwd} := D/K_{opt}$ (* adapted forwarding distance *)
3: $A := N_1$ (* initialize A *)
4: $\Delta := |distance(S, N_1) - d_{fwd}|$ (* deviation *)
5: **for** $i := 2, \ldots, k$ **do**
6: $\quad \Delta' := |distance(S, N_i) - d_{fwd}|$ (* deviation *)
7: $\quad$ **if** $\Delta' < \Delta$ **then**
8: $\quad\quad A := N_i$ and $\Delta := \Delta'$
9: $\quad$ **end if**
10: **end for**
11: **return** A

hops K_{opt} is computed via Algorithm 1 (line 1) followed by the computation of the adapted forwarding distance d_{fwd} (line 2). The remainder of Algorithm 3 (lines 3 to 11) is identical to Algorithm 2, except that d_{fwd} is used instead of d_{char} to determine the next hop.

Our evaluation reveals that AMERR consumes less power than MERR. In fact, for a Poisson rate of 0.10 or greater, AMERR achieves optimal performance. This improvement comes with a lower degree of locality, because in AMERR a sensor node must be aware of its distance to the base station. If this additional constraint is consistent with the application, AMERR should still be favored over MERR.

5.3 Two-Dimensional Sensor Networks

Our proposed protocols are designed for linear WSNs. They are therefore directly applicable to sensor networks with an intrinsic linear topology, such as those used for structural health monitoring of bridges and pipelines. Both algorithms can also be used for routing in linear WSNs that are part of a two-dimensional network. Consider, for example, a building where sensor nodes are deployed along corridors and base stations are deployed at corridor intersections serving as gateways. A possible application could be automated aeration and lighting control. In this scenario, the entire network is composed of several linear subnetworks in which MERR and AMERR may be used to transfer data to the nearest base station.

MERR and AMERR can also be generalized to arbitrary two-dimensional WSNs. Unlike linear WSNs, routing is not directed just by itself in those networks; it must be ensured by the routing protocol that the next hop is made toward the base station. One possibility to extend MERR and AMERR to that effect is to adapt the notion of progress. Progress is made if the next node on the routing path is closer to the destination than the current node. Obviously, we would like to maximize the progress and at the same time select that node whose distance from the current node deviates least from the characteristic distance (MERR) or the adapted forwarding distance (AMERR). If a sensor S is aware of its distance to the destination D, d_{SD}, as well as the distances of its neighbors, say A, to the destination D, d_{AD}, the progress made if S forwards to A can be defined as the difference of these two distances, $d_{SD} - d_{AD}$. Consequently, S selects neighbor A that minimizes $\Delta/(d_{SD} - d_{AD})$, where Δ denotes the deviation of the distance between S and A from the characteristic distance (MERR) or the adapted forwarding distance (AMERR).

Table 1: Radio and network parameters.

Parameter	Value
α_{rx}	50 nJ/bit
α_{tx}	50 nJ/bit
α	100 nJ/bit
γ	2 and 4
ϵ ($\gamma = 2$)	10 pJ/bit/m^2
ϵ ($\gamma = 4$)	0.0013 pJ/bit/m^4
r	1 bit/s
d_{char} ($\gamma = 2$)	100 m
d_{char} ($\gamma = 4$)	71 m
n	100

6. EVALUATION

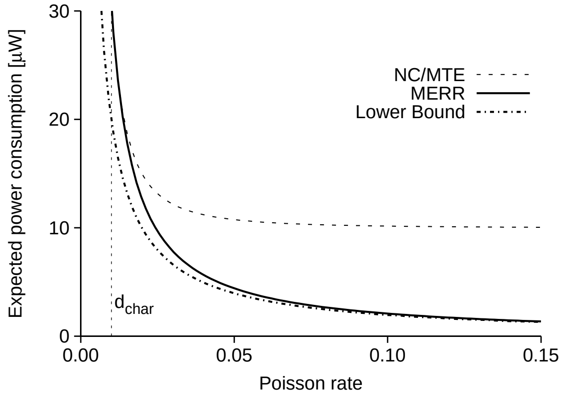
We now present a twofold evaluation of our proposed protocols. The first part involves a discussion of our stochastic analyses, where we compare the expected power consumption of MERR with the optimal lower bound and the NC/MTE method. Subsequently, we present simulation results showing the performance of MERR and AMERR compared to the localized routing algorithms described in Section 2. Table 1 summarizes radio characteristics and network parameters, adopted from [11], which we use for the stochastic analyses as well as the simulations.

Let us first consider the two graphs in Figure 6. They show the expected power consumptions of MERR (see Theorem 3), the optimal lower bound (see Theorem 2), and the NC/MTE algorithm for relaying a bit-stream with unit rate from node n to the base station. The corresponding expression for NC/MTE is

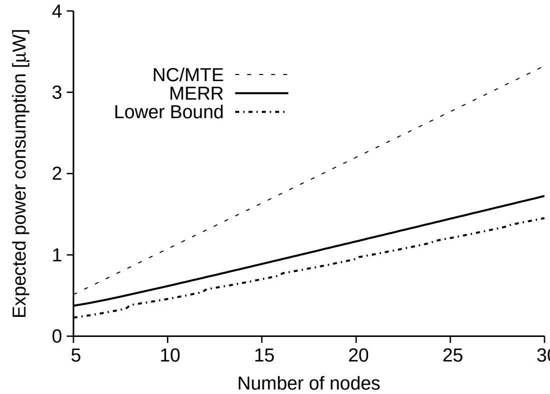
$$\mathbb{E}[P_{MTE}(X_n)] \;=\; -\alpha_{rx} + n\left(\alpha + \frac{\Gamma(\gamma+1)\,\epsilon}{\lambda^{\gamma}}\right), \qquad (21)$$

where X_n is the distance of node n to the base station. Figure 6(a) shows expected power consumption depending on the Poisson rate for a network of 100 nodes. A greater Poisson rate implies a higher node density (number of nodes per length unit) in the linear network. First, it can be seen that MERR is upper-bounded by NC/MTE. The reason for this is that for Poisson rates smaller than 0.01, the distances between adjacent nodes are on average equal or longer than the characteristic distance. In this case, a sensor running MERR selects the neighbor closest to itself just as with NC/MTE. Thus, both algothims have equal power consumption. Second, we note that MERR rapidly approaches the optimal lower bound as the Poisson rate increases. This is because greater Poisson rates imply higher node densities, thus making it more likely to find a path that well approximates the optimal path. Figure 6(b) shows expected power consumption depending on the number of nodes for a Poisson rate of 0.04. We can see that the power consumption of MERR scales linearly with the number of nodes, which is the best case with regard to scalability. The slopes of the curves of MERR and the optimal lower bound are almost the same.

In addition to the stochastic analyses, we carried out simulations to compare the power consumption of our proposed protocols to other well-known approaches. The simulations are designed as follows. Linear networks with 100 nodes are generated with varying Poisson rates. The choice of 100



(a) Depending on Poisson rate (100 nodes).



(b) Depending on number of nodes (0.04 Poisson rate).

Figure 6: Expected power consumption of MERR and NC/MTE compared to the lower bound for $\gamma = 2$.

seems reasonable for deployments at long bridges or along pipelines. The neighborhood of a sensor is defined by its maximum transmission radius, which we assume to be twice the length of the characteristic distance. Only connected networks are considered, that is, each sensor has at least one downstream neighbor. The comparison of the various protocols is based on *power dilation*, which we define as the ratio of the power consumption of a specific protocol to that of the optimal lower bound. The final results are averages over 100 generated networks. Tables 2 and 3 show the power dilations of the considered algorithms with varying Poisson rate for path loss exponent 2 and 4, respectively. The Poisson rates 0.01, 0.02, 0.05, 0.10, 0.20, and 0.40 correspond to 100 m, 50 m, 20 m, 10 m, 5 m, and 2.5 m of average distance between adjacent nodes.

The power dilation of NC/MTE increases rapidly with greater Poisson rates, because all nodes are used for relaying the data from the source node to the base station. This dissipates immoderate receive energy, particularly if nodes are close to each other. Greedy/MFR performs better with only slightly increasing dilation for greater Poisson rates. The crucial parameter for Greedy/MFR is the maximum transmission radius of a sensor node. The further a sensor can transmit, the higher the transmitting power needed to reach the selected neighbor. If the maximum transmission radius is around the characteristic distance, Greedy/MFR has performance close to the lower bound. For longer radii, however, immoderate power is dissipated for transmitting.

Progress and Progress Vector have equal power consumption, because both algorithms make the same routing decisions in a linear sensor network. In Progress, the advance toward the base station B when sending from some sensor S to node A is the distance between S and A, d_{SA}. In Progress Vector, the advance is calculated via the dot product of the two vectors SA and SB, which equates to the product of the distances $d_{SA} \cdot d_{SB}$. Hence, in a linear network, the advance in Progress Vector is equal to the advance in Progress scaled by the constant factor d_{SB}. Up to a Poisson rate of 0.01, Progress and Progress Vector have power dilations comparable to Estimation, MERR, and AMERR. For greater Poisson rates, their performance is slightly inferior. We presume that this due to the fact that, unlike the other three algorithms, Progress and Progress Vector do not separately handle the case that the base station is a neighbor of the node currently holding the message. That is, data are forwarded to an intermediate node even though direct transmission to the base station would consume less power. This becomes more prejudicial with increasing Poisson rate.

Independent of the Poisson rate, MERR performs as least as good as the Estimation algorithm. Although the power savings are marginal, the real improvement of MERR is with respect to protocol complexity, localization, and scalability. A node running the Estimation protocol must be aware of the distances to its neighbors, the distance to the base station, plus the respective distances from its neighbors to the base station (needed to estimate the power consumed on the remaining path from the neighbor). As for Progress, the distances to neighbors and the distance to the base station are required. In order to compute with vectors in Progress Vector, a node even has to know the exact locations of its neighbors and the base station with respect to a global coordinate system. These constraints might be very difficult to fulfill and are therefore a limiting factor in particular for large-scale sensor networks. Furthermore, the necessary computations are quite intensive. In MERR, a node only has to know the distances to its downstream neighbors and the characteristic distance, which is a constant for all nodes in the network. The routing decisions are made by simple computations. Thus, MERR is highly localized and induces minimal protocol overhead. The effort to be made after a node has joined the network or has changed its position is limited to localized information exchange with neighbors. Even in presence of node mobility, MERR allows for self-managing and power-efficient operation of sensor networks consisting of thousands of nodes.

Finally, we note that AMERR consumes less power than all other algorithms and has almost ideal performance for Poisson rates greater than 0.10. Using Algorithm 1, AMERR computes the exact optimal number of hops, allowing a more precise selection of the next hop. This leads to reduced power consumption, particularly for greater Poisson rates (higher node densities). As mentioned before, this improvement comes with the additional constraint that nodes must know their distance to the base station. Depending on the application at hand, this might be feasible or not and either MERR or AMERR can be implemented.

Table 2: Power dilations for $\gamma = 2$.

λ	NC/MTE	Greedy/MFR	Estimation	Progress Progress Vector	MERR	AMERR
0.01	1.28	1.14	1.08	1.08	1.08	1.08
0.02	1.52	1.15	1.05	1.05	1.05	1.05
0.05	2.75	1.18	1.02	1.02	1.02	1.01
0.10	5.30	1.21	1.02	1.03	1.01	1.00
0.20	10.99	1.21	1.02	1.05	1.01	1.00
0.40	23.19	1.18	1.02	1.09	1.01	1.00

Table 3: Power dilations for $\gamma = 4$.

λ	NC/MTE	Greedy/MFR	Estimation	Progress Progress Vector	MERR	AMERR
0.01	1.60	1.66	1.35	1.36	1.35	1.35
0.02	1.74	1.69	1.25	1.26	1.25	1.25
0.05	2.88	1.85	1.07	1.08	1.07	1.07
0.10	5.57	2.01	1.03	1.05	1.03	1.02
0.20	11.68	2.06	1.03	1.07	1.03	1.01
0.40	24.58	1.92	1.03	1.12	1.03	1.00

7. CONCLUSIONS

In this paper, we motivate two localized power-aware routing protocols for linear topology WSNs. Linear topology networks often appear in pipeline monitoring and structural health monitoring, but the application that motivated this work is telemetry and control for freight railroad trains. Using sensor networks to provide more timely information, the goal of this commercial application is to attain greater visibility of the rolling assets and cargo to allow for realtime failure prediction of a train's components. Because the maintenance cost of the WSN infrastructure should not add appreciably to the existing maintenance costs, the sensor network should organize and manage itself in an energy-efficient manner. Moreover, much of the energy of a WSN is consumed during routing, as routing involves several nodes each of which should process and communicate sensed data.

Our routing schemes take into account the channel characteristics, the radio component, and the distribution of the sensor nodes along a linear path modeled by a one-dimensional homogeneous Poisson process. Based on these parameters and assumptions, we set a theoretical optimal lower bound of routing in a linear WSN. We evaluate the efficiency of our protocols with respect to the optimal lower bound and with respect to other existing protocols. For a Poisson rate of 0.10 or greater, AMERR achieves optimal performance, while MERR rapidly approaches optimal performance as the Poisson rate increases. Compared to other protocols, we show that MERR and AMERR are less complex and have better scalability. We also postulate how MERR and AMERR might be generalized to a two-dimensional WSN.

At present, our routing protocols do not take into account fairness. This is rather an important parameter because it ensures that nodes exhaust their energy uniformly throughout network operation. Otherwise, some nodes located on a single optimal path may drain out of energy quickly, leading to sudden partition of the network. In the future, we are planning to include fairness metrics as well to address this problem.

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