The Myth of Power Control in Routing

Cigdem Sengul Robin Kravets

Department of Computer Science
University of Illinois Urbana-Champaign
sengul@uiuc.edu, rhk@cs.uiuc.edu

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Abstract

Energy management remains a critical problem in ad hoc networks since battery technology cannot keep up with rising expectations in wireless communications. Current approaches to energy conservation focus on reducing the energy consumption of the wireless interface either for a given communication task or during idling. However, these *communication-time* and *idle-time* approaches are not necessarily complementary. Therefore, we explore the interactions between the two approaches and their impact on the design of a complete solution to energy conservation. Essentially, a complete solution requires minimizing the energy spent in communication (i.e., for data and control overhead) and in idling while satisfying communication needs. This problem can be expressed as an energy-efficient network design problem, which is, not surprisingly, NP-hard. Therefore, we study several *heuristic* approaches. Our study shows that minimizing energy consumed in data transmissions as a primary goal does not save energy. Furthermore, jointly reducing energy consumed for both data and in idling becomes cost-prohibitive when the energy spent in control overhead is considered. Hence, we propose a two-stage approach that prioritizes idling energy consumption over energy spent for data transmissions. Due to its low control overhead, this two-stage approach provides an effective way to meet the challenge of operating the network with low energy cost.

1 Introduction

Energy management is one of the greatest challenges in wireless networks due to the continuous increase in the energy requirements of wireless devices and the slow advancement of battery technology. Therefore, it is essential to incorporate energy efficiency into the design of network protocols. Current research has focused on communication-time energy conservation, which aims to optimize the use of the wireless interface for a given communication task, or idle-time energy conservation, which aims to optimize the energy consumption when the wireless interface is idle. Obviously, a complete solution needs to conserve energy during both communication and idle times. However, the complex interactions between communication-time and idle-time energy conservation techniques present a significant challenge. To this end, this paper explores the limits of traditional stand-alone approaches and exposes some commonly held myths about energy conservation.

Since communication and idle times are disjoint, communication-time and idle-time approaches are typically considered to be complementary [1, 2]. Unfortunately, joint utilization of these two approaches is likely to exhibit negative interactions. Consider two techniques: energy-aware routing using transmission power control (TPC) and power management. TPC allows tuning the transmission power level based on the distance between the sender and the receiver. Due to non-linear power attenuation, transmitting via more short hops may result in a lower energy consumption than via one long hop. Hence, energy-aware routing exploits TPC and routes through multiple short hops to reduce communication energy. Power management, on the other hand, saves idle-time energy by allowing nodes to switch to a *power-save mode (PSM)*, in which a node spends *most* of its time in a low-power sleep state [3, 4]. The negative interaction occurs since energy-aware routing saves energy at the expense of using more relay nodes and power management saves energy by eliminating the use of redundant relay nodes. In this paper, we expose such interactions and show how these interactions impact the design of a complete solution to energy conservation.

Minimizing energy consumption due to both communication (i.e., data and control overhead) and idling while satisfying network traffic constraints is an energy-efficient network design problem, which is, not surprisingly, NP-hard [5, 6]. Furthermore, designing approximation algorithms that allow distributed and online

implementations is extremely challenging [5], leaving a *heuristic* approach as the only option. The main contribution of our research is an in-depth analysis of three such approaches: (1) minimizing communication-time energy use as a primary goal, (2) jointly optimizing for both communication-time and idle-time energy use and (3) minimizing idle-time energy use as a primary goal. Our analysis shows that the first approach is not practical for current wireless cards and the control overhead of the second approach does not support scalable solutions. As a result, we propose a new two-stage approach to energy-efficient network design that reduces idling costs as a primary goal and communication costs as a secondary goal. Our extensive evaluation verifies that the two-stage approach meets the challenge of operating the network with low energy cost without degrading communication performance.

The rest of the paper is organized as follows. In the next section, we present an energy model that supports the evaluation of the energy-efficiency of communication-time and idle-time energy conservation. In Section 3, we formally define the energy-efficient network design problem and in Section 4, we describe the three heuristic approaches to this problem in detail. Performance evaluation results are presented in Section 5. Finally, Section 6 presents concluding remarks and gives possible directions for future work.

2 Energy-Aware Operation in Ad Hoc Networks

To support energy-awareness in ad hoc networks, it is essential to understand the energy trade-offs in wireless communication. To this end, we present an energy model based on the energy characteristics of wireless cards and node participation in the network. Next, we use this model to highlight the limitations of two prominent techniques for communication-time and idle-time energy conservation.

2.1 Energy Model

The energy consumption of a network is determined by the amount of energy spent by all nodes. The energy consumption of each node i is the sum of its communication-time energy (i.e., when it is transmitting or receiving), $E_{active}(i)$, and its idle-time energy (i.e., when it is not engaged in communication), $E_{passive}(i)$. Obviously, $E_{active}(i)$ and $E_{passive}(i)$ are strongly tied to the energy characteristics of a wireless card and the node's participation in the network.

The energy characteristics of a wireless card are determined by its operating modes: *transmit*, *receive*, *idle* and *sleep*. While *transmit* is the most power-hungry mode, to compensate for this, current wireless cards support a range of transmit power levels. *Sleep* power is typically negligible. *Idle* power is as large as *receive* power and is identified as the dominating factor for energy consumption in wireless communication [7]. In addition to the power for each radio mode, $E_{active}(i)$ and $E_{passive}(i)$ are also a function of the time spent in each state, which in turn depends on many factors, including traffic load, routing decisions and packet failures.

For each node i, $E_{active}(i)$ is the sum of the energy consumed for data and control overhead, $E_{data}(i)$ and $E_{control}(i)$, respectively. Given the total time spent in data reception, $t_{rx}^{data}(i)$, and the time spent transmitting to each node j, $t_{tx}^{data}(i,j)$, $E_{data}(i)$ is:

$$E_{data}(i) = t_{rx}^{data}(i) \cdot P_{rx} + \sum_{j \in NextHop} t_{tx}^{data}(i,j) \cdot P_{tx}(i,j), \tag{1}$$

where the receive power is P_{rx} and the transmission power, $P_{tx}(i,j)$, is determined by the transmit power level to reach node j. More formally, $P_{tx}(i,j) = P_{base} + P_t(i,j)$, where P_{base} is the base transmitter cost and $P_t(i,j)$ is the transmit power level. $P_t(i,j)$ attenuates with the n^{th} power of the distance between nodes

i and j, where n is the path loss exponent and $2 \leq n \leq 4$ depending on channel characteristics. Since P_{rx} and P_{base} are fixed costs, $E_{data}(i)$ is determined by how much data a node relays and the transmission costs defined by the $P_{tx}(i, j)$'s.

Given the time spent in receiving and transmitting control packets, t_{rx}^{ctrl} and t_{tx}^{ctrl}, respectively, $E_{control}(i)$ is:

$$E_{control}(i) = t_{rx}^{ctrl}(i) \cdot P_{rx} + t_{tx}^{ctrl}(i) \cdot P_{tx}^{max}. \tag{2}$$

We assume that control packets are transmitted with maximum power level, P_t^{max}, and so use P_{tx}^{max} for transmission. From (2), it is easy to see that $E_{control}$ can only be reduced by limiting control overhead.

$E_{passive}(i)$ represents the energy consumed when a node is not involved in reception or transmission. During this time, the wireless interface of a node can be in a sleep state with sleep power, P_{sleep}, for a duration of t_{sleep} or in an idle state with idle power, P_{idle}, for a duration of t_{idle}. Therefore,

$$E_{passive}(i) = t_{idle}(i) \cdot P_{idle} + t_{sleep}(i) \cdot P_{sleep} + E_{switch}, \tag{3}$$

where E_{switch} captures the energy cost involved in deciding when to switch to a sleep state. Obviously, $E_{passive}(i)$ is minimized if the network interface switches to a sleep state as soon as the node becomes idle.

Based on this node-based energy model, the network energy consumption, $E_{network}$ is defined as:

$$E_{network} = \sum_{i=1}^{m} E_{active}(i) + E_{passive}(i), \tag{4}$$

where m is the number of nodes. Using this energy model, we next evaluate the impact of communication-time and idle-time energy conservation on total energy consumption.

2.2 Communication-Time vs. Idle-Time Energy Conservation

Energy conservation approaches in wireless networks target energy spent in specific modes of a wireless card. Due to the high power of transmit mode, much research has been directed at minimizing the per-hop transmit power level, $P_t(i, j)$, via transmission power control. Since $P_t(i, j)$ increases with the n^{th} power of the distance, even though node i and node j can communicate directly, it is less energy consuming to send from node i to node j through multiple hops with shorter distances. Therefore, energy-aware routing (e.g., PARO [8], MTPR [9]) uses $P_t(i, j)$ as a cost metric to discover such routes. However, the main goal is saving energy from $\sum_i E_{data}(i)$, and the effects on $\sum_i E_{control}(i)$ and $\sum_i E_{passive}(i)$ are ignored.

Since $E_{passive}(i)$ is the dominating energy consumer when there is no communication [10], power management is a well-adopted idle-time energy conservation technique. Using power management, a node can be in one of two modes, *power-save mode (PSM)* and *active mode (AM)*. In PSM, a node keeps its wireless card mostly in sleep state and switches it to idle to check for data (e.g., IEEE PSM [11]). In AM, a node is either transmitting, receiving or idling. While PSM may benefit lightly-loaded networks, it severely limits network capacity as the load increases [4]. Therefore, power management approaches enforce a AM/PSM duty cycle on nodes. Transitions between PSM and AM can be triggered based on traffic duration (e.g., ODPM [4]) or topology (e.g., Span [3]) or both (e.g., TITAN [12]). However, power management only optimizes for $\sum_i E_{passive}(i)$ and ignores $\sum_i E_{active}(i)$.

Both energy-aware routing and power management optimize for different radio states in isolation, which prohibits obtaining the full benefits of energy conservation. Therefore, we next study the joint utilization of these approaches as an energy-efficient network design problem.

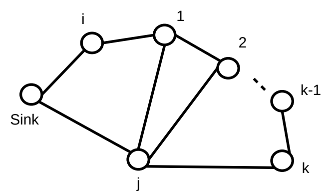

Figure 1: Example network.

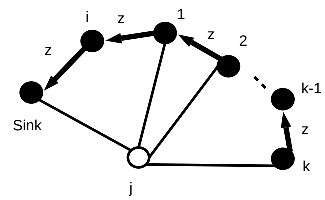

Figure 2: Steiner Tree 1.

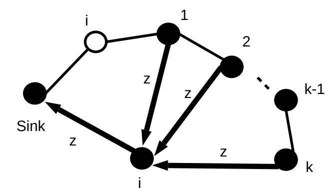

Figure 3: Steiner Tree 2.

3 Energy-Efficient Network Design

The *energy-efficient network design* problem is similar to traditional network design problems, which, given a weighted graph, ask for a subgraph of minimum total weight satisfying some connectivity requirements [13]. In this section, we give a formal definition of the problem, which is NP-hard. Although a constant-bound approximation applies to a simplified version of this problem [5], we show through a simple example that the quality of solutions found might deviate significantly, necessitating the design of new solutions.

We model a wireless network as a weighted undirected graph $G = (V, E, c(v), w(e))$, where V is the set of nodes, and E is the set of undirected edges (i.e., $(u, v) \in E$ if u can transmit to v, and vice versa). Node and edge weights are $c(v)$ and $w(e)$, respectively. Essentially, $c(v)$ is either P_{idle} or P_{sleep} based on the power management state of a node v, whereas $w(e)$ is determined by the power to transmit over link (u, v), $P_{tx}(u, v)$ and the power for receiving, P_{rx}.

Connectivity requirements of source and destination nodes can be represented by a traffic demand matrix T, where $T = \{(s_i, d_i, r_i)|(s_i, d_i) \in S\}$ and S is a set of source-destination pairs. Hence, associated with each pair (s_i, d_i), there is a nonnegative, real valued traffic demand r_i. Essentially, this demand matrix provides the flexibility to represent multicast, broadcast and unicast traffic.

Based on this notation, the energy-efficient network design problem can be defined as follows:

Definition 1 *Given a network $G = (V, E, c(v), w(e))$, the goal of energy-efficient network design is to find a subgraph F, such that:*

1. $\forall(s_i, d_i, r_i > 0)$ s_i *is connected to* d_i *in* F *(i.e., there is a path from* s_i *to* d_i *in* F*)*

2. $E_{network}$ *is minimized.*

We simplify the definition of $E_{network}$ to represent only idling and data transmission and reception costs:

$$E_{network} = \sum_{u,e \in F} t_{idle}(u) \cdot c(u) + t_{data}(e) \cdot w(e), \tag{5}$$

where $t_{data}(e)$ is the time spent in data communication. Energy costs from control overhead, sleeping and E_{switch} are ignored. (This simplification is only made for the analysis and not in the rest of paper.) While the energy spent in sleeping is negligible, E_{switch} can be amortized using reasonable a sleep scheduling mechanism. The energy cost of control overhead is determined by the complexity of the algorithm that finds the optimal solution to energy-efficient network design, if it exists.

Essentially, energy-efficient network design is the problem of constructing a node-weighted Steiner forest (considering node and edge disjoint routes) and hence, is NP-hard [14]. A constant approximation

algorithm, MPC (Minimum Power Configuration), has been proposed for a *simplified version* of this problem for multiple sources and a single sink [5]. Essentially, a constant-bound approximation is possible if link cost, $w(e)$, is bounded by node cost, $c(u)$ (i.e., $w(e) \leq \alpha \cdot c(u)$) and $c(u)$ is constant. Executing a minimum-weight Steiner tree approximation algorithm in this graph, with no node weights and with edge weights equal to $c(u)$, leads to an algorithm with an approximation ratio of $1 + \alpha$. However, even within this constant bound, the quality of solutions generated by MPC might deviate significantly in terms of $E_{network}$. We next illustrate this through a simple example.

In the network depicted in Fig. 1, there is one sink node, k sources, and nodes i and j. Two minimum-weight Steiner trees in the network for k sources, denoted $ST1$ and $ST2$, are shown in Figs. 2 and 3. Both trees are potential output of MPC. We next evaluate $ST1$ and $ST2$ based on their respective $E_{network}$.

Consider the case where each source generates one packet to send to the sink, link activity for one packet lasts t_{data} and each node stays idle for a duration of t_{idle}. Given $P_{tx}(u,v) = \alpha \cdot z$, $P_{rx} = P_{idle} = z$, $E_{network}$ of $ST1$, E_{ST1}, is:

$$E_{ST1} = (k+1) \cdot t_{idle} \cdot z + k \cdot \frac{(k+3)}{2} \cdot t_{data} \cdot (\alpha + 1) \cdot z. \tag{6}$$

The second term of the equation is calculated by observing that node k transmits 1 packet, node $k-1$ transmits 2 packets, and node l transmits $k-l+1$ packets. The relay node i transmits k packets. Therefore, there is a total of $k \cdot \frac{k+3}{2}$ transmissions.

Similarly, $E_{network}$ of $ST2$, E_{ST2}, is:

$$E_{ST2} = (k+1) \cdot t_{idle} \cdot z + 2 \cdot k \cdot t_{data} \cdot (\alpha + 1) \cdot z. \tag{7}$$

Again, the second term of the equation is calculated by observing that k sources transmit one packet and the relay node j transmits k packets.

Comparing E_{ST1} to E_{ST2},

$$\frac{E_{ST1}}{E_{ST2}} = \frac{(k+1) \cdot t_{idle} + k \cdot \frac{(k+3)}{2} \cdot (\alpha+1) \cdot t_{data}}{(k+1) \cdot t_{idle} + 2 \cdot k \cdot (\alpha+1) \cdot t_{data}}. \tag{8}$$

The ratio of E_{ST1} to E_{ST2} is affected by t_{idle} and t_{data}. It is easy to see that E_{ST1} and E_{ST2} are equivalent if t_{idle} is the dominating factor (e.g., when nodes do not use power management and traffic load is low). If we assume that nodes switch immediately to sleep after each transmission, $t_{idle} = 0$ and E_{ST1} and E_{ST2} are determined by transmission costs. In this case, $\frac{E_{ST1}}{E_{ST2}} = \frac{k+3}{4}$. Therefore, the $E_{network}$ performance of MPC can deviate with the number of sources. This shows that the structure of a Steiner tree and its impact on communication needs to be considered in addition to the number of nodes and links on this tree.

In this section, we showed that even when traffic demands are restricted to many-to-one communication, current approximation algorithms might produce solutions that differ significantly in terms of $E_{network}$. We made several assumptions to simplify the analysis. In ad hoc networks, packet transmissions are not perfect, the traffic demand, typically, cannot be determined in advance and a centralized solution is not acceptable. However, designing distributed and online approximation algorithms for this problem is, obviously, challenging. Therefore, next, we systematically study three heuristic approaches that are not limited by these assumptions.

4 Heuristic Approaches

Interpreting energy-efficient network design as a multi-objective optimization problem opens the door for different heuristic approaches. Given the two objectives of minimizing communication-time energy and

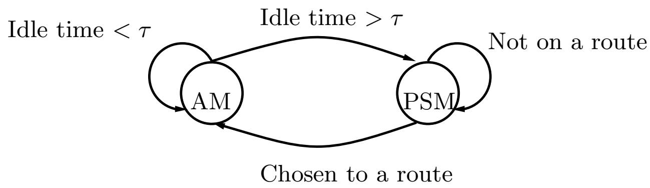

Figure 4: Power management state transition in ODPM.

idle-time energy, we can either prioritize one objective over the other or fuse the two objectives into one. In this section, we study three natural heuristics: (1) minimize communication-time energy first, (2) jointly optimize communication-time and idle-time energy and (3) minimize idle-time energy first. In this section, we present the design details of these approaches highlighting their benefits and drawbacks, and present their performance evaluation in Section 5.

4.1 Minimize Communication-Time Energy First

Since transmission power attenuates polynomially with distance, multiple transmissions over short distances are expected to save energy in comparison to one direct transmission. Therefore, we first consider energy-aware routing using power control as the primary optimization technique for energy-efficient network design. Once the relay nodes that minimize transmission costs are chosen, the rest of the nodes switch to a power-save mode through power management.

We implement this approach using MTPR (Minimum Transmission Power Routing) for routing and using ODPM for power management. Once a node is chosen as a relay by MTPR, ODPM keeps this node in active mode using a *keep-alive timer* as long as the node is forwarding traffic (see Fig. 4). We experiment with two flavors of MTPR: MTPR and MTPR+. While MTPR uses purely transmit power level as the routing metric, MTPR+ also takes base transmit and receive power costs into account. More formally, the cost functions used in MTPR and MTPR+ are as follows:

$$MPTR : f(u,v) = P_{tx}(u,v) \tag{9}$$
$$MPTR+ : f(u,v) = P_{base} + P_{tx}(u,v) + P_{rx} \tag{10}$$

MTPR is implemented as a reactive routing protocol. Different than traditional MANET protocols, in MTPR route requests (RREQs) need an extra field to store the sum of $f(u,v)$'s along the route. When a node receives a RREQ for the first time, it updates the cost of the route using the transmit power level and rebroadcasts the packet. Duplicate RREQ packets may be rebroadcast and multiple route replies may be sent, if they advertise a lower energy cost. In addition to route discovery, routing tables must be modified to store the energy cost of each route. We implement the proposed changes over DSR. The route snooping option of DSR is disabled due to potential inefficiencies from not having a list of $f(u,v)$'s for each hop.

This approach tries to find routes with lower communication costs at the cost of increased routing overhead. However, in addition to this trade-off, idling energy is also expected to increase, which might impair the beneficiality of this approach.

4.2 Heuristic for Joint Optimization

Incorporating both power control and power management into a routing protocol might enable higher energy savings by minimizing both node and links costs. Essentially, given two routes with the same number

of relay nodes, total energy consumption is minimized when the route with minimum link cost, which is determined by the $P_t(i,j)$'s, is chosen. To construct routes based on both node and link costs, a natural cost function is $h(u,v)$ [5]:

$$h(u,v) = \begin{cases} (P_{tx}(uv) + P_{rx} - 2 \cdot P_{idle}) \cdot \frac{r_i}{B}, & \text{if } i \text{ in AM} \\ (P_{tx}(uv) + P_{rx} - 2 \cdot P_{idle}) \cdot \frac{r_i}{B} + P_{idle}, & \text{if } i \text{ in PSM} \end{cases} \tag{11}$$

where the rate of a flow between a source s_i and destination d_i is r_i and bandwidth is B. $P_{tx}(u,v)$ is determined at transmission time using the RTS-CTS exchange at the MAC layer. When the rate information is not available, $h(u,v)$ is modified by setting $\frac{r_i}{B} = 1$, which, however, does not capture the impact of traffic rate on link costs. Next, we describe how $h(u,v)$ can be applied to proactive and reactive routing.

Proactive routing using $h(u,v)$: To use the $h(u,v)$ metric, it is necessary to modify the routing table structure and the route look-up. Each node needs to keep information about the power management state of its neighbors and the transmit power levels to reach each neighbor. If available, s_i includes r_i in each packet header, and so, there is no need to maintain this information in the routing tables. Obviously, based on different node and link costs, multiple entries for each destination might exist. When forwarding a packet for source s_i, node u chooses the best next-hop node by finding an entry with minimum $node\_cost + r_i \cdot link\_cost$. We implement these modifications based on DSDV [15], similar to MPC [5]. However, MPC implements the $h(u,v)$ heuristic for a many-to-one scenario and proposes a different routing table structure, which requires a route update whenever the rate of a flow changes. In our implementation, a route update only needs to be triggered when the quality of a link or the power management state of a node changes. Hence, our approach to using $h(u,v)$ in DSDV for a many-to-many scenario incurs less control overhead. Therefore, we do not consider MPC in our evaluations.

Reactive routing using $h(u,v)$: To accommodate the $h(u,v)$ metric, it is necessary to modify route discovery and routing table maintenance. The modifications are similar to ones in MTPR; however, different than MTPR, when a node receives a RREQ for the first time, it updates the cost of the route using the transmit power level *and its power management state information* and rebroadcasts the packet.

In both reactive and proactive implementations, the joint-optimization approach tries to explore paths with less energy consumption at the cost of increased routing messages. Therefore, in a dynamic network environment, this approach is susceptible to producing an overwhelming amount of control traffic to track link cost changes.

4.3 Power Management as Primary Optimization

Since link costs are prone to rapid fluctuations due to environmental factors, using such costs as a part of a routing metric may result in unstable routes, which in turn results in high routing overhead. Therefore, the final approach first minimizes node costs and second link costs. To support power management as a primary optimization, we propose a two-stage protocol design. The goal of the first stage is to minimize the number of relay nodes. In the second stage, selected nodes stay active and use TPC to minimize the link costs to reach their neighbors.

We implement two prototypes of our two-stage approach based on two different protocols for node selection. In the first prototype, the relay nodes are simply determined by a reactive shortest-path routing algorithm, which is DSR in our implementation. Once a node is chosen as a relay, ODPM maintains the

power management state of the node based on its current participation in routing. In the second prototype, an on-demand topology management protocol, TITAN [12], is used to select relay nodes. ODPM might activate redundant nodes and TITAN addresses this shortcoming by maintaining a backbone of nodes. The basic idea is to favor nodes that are already in active mode as good candidates for routing, so that the nodes in power-save mode can continue sleeping. When route diversity in the network is low, both protocols are expected to behave similarly. However, as route diversity increases, TITAN reduces the number of relay nodes.

Essentially, our two-stage approach provides a low-complexity solution to energy-efficient network design. Through this low complexity, it is possible to obtain low communication costs, which is the key to achieving high energy savings without degrading communication performance.

5 Performance Evaluation

In this section, we present the first comprehensive study of energy-efficient network design by investigating three heuristic approaches introduced in Section 4. Through analytical study, we first rule out the first approach (i.e., minimize communication-time energy first) showing that it does not provide energy savings for current wireless cards. Next, we evaluate second and third approaches (i.e., joint optimization and power management as primary optimazation, respectively) via a simulation study. Finally, we extend our simulation study to a hypothetical wireless card to evaluate if the first approach provides any energy savings in comparison to the second and third approaches.

5.1 Analytical Study

To understand the effectiveness of power control as a primary optimization, it is necessary to analyze if and when energy savings can be obtained by using relays between a source and a destination that are *in transmission range of each other* rather than direct transmission. Obviously, the degree to which energy efficiency can be attained is limited by radio design. Hence, based on the radio parameters, we determine the optimal hop count that justifies using the transmission power level as a routing metric. The steps to derive this optimal hop count are similar to [16, 17], where *characteristic distance* is introduced as the optimal hop distance that minimizes the energy cost of end-to-end transmission. However, the derivation of characteristic distance ignores $E_{passive}(i)$, and therefore, is only a function of transmission power, $P_{tx}(i,j)$, reception power, P_{rx}, and the path loss exponent [16]. This omission is addressed in [17]. However, the relationship between transmission range and characteristic distance is not considered. Essentially, characteristic distance might be greater than the transmission range, in which case only direct transmission is feasible. To capture this effect of transmission range on optimal hop count, we define the *characteristic hop count* as the optimal number of hops between two nodes that are in transmission range of each other.

To derive characteristic hop count, we analyze the total energy consumption from an end-to-end transmission, E_{route}. Using equations from Section 2.1,

$$E_{route} = \sum_{i}^{m+1} E_{active}(i) + E_{passive}(i), \tag{12}$$

where $i = 1$ is the source and $i = m + 1$ is the destination, and there are $m - 1$ relays. We assume that the nodes on the route are in active mode, and hence, $t_{sleep} = 0$ and $E_{switch} = 0$. Ignoring $E_{control}(i)$,

$$E_{route} = \sum_{i=1}^{m} t_{tx}^{data}(i) \cdot P_{tx}(i, i+1) + t_{rx}^{data}(i) \cdot P_{rx} + t_{idle}(i) \cdot P_{idle}. \tag{13}$$

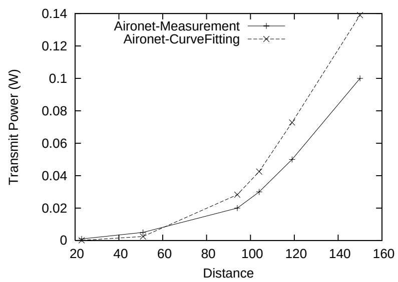

Figure 5: Transmission power model for Aironet 350. Curve fitting vs measurement.

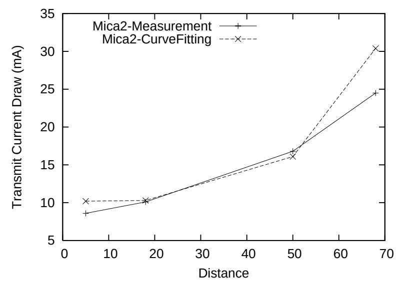

Figure 6: Transmit current draw model for Mica2 mote measurements.

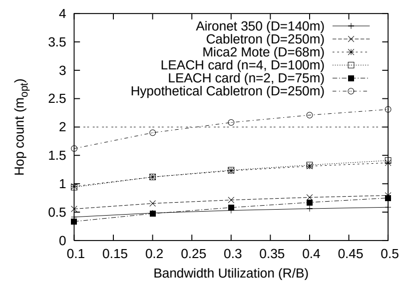

Figure 7: Characteristic hop count for Aironet 350 and Cabletron.

Table 1: Radio parameters for current cards (mW)

Cards	P_{idle}	P_{rx}	$P_{tx}(d)$
Aironet 350 [18]	1350	1350	$2165 + 3.63 \cdot 10^{-7} \cdot d^4$
Cabletron [3]	830	1000	$1118.2 + 7.2 \cdot 10^{-8} \cdot d^4$
Hypothetical			$1118.2 + 5.16 \cdot 10^{-6} \cdot d^4$
Mica2 mote [19]	21	21	$10.2 + 9.44 \cdot 10^{-7} \cdot d^4$
LEACH (1Mb/s)	$x \cdot 50$	50	$50 + 1.3 \cdot 10^{-6} \cdot d^4$ $50 + 10^{-2} \cdot d^2$

For a given rate R, bandwidth B, and time t, $t_{rx}^{data}(i) = t_{tx}^{data}(i) = \frac{R}{B} \cdot t$, except $t_{rx}^{data}(1) = 0$ and $t_{tx}^{data}(m+1) = 0$. The remainder of t is spent in idling. Since $P_{tx}(i, i+1)$ is a function of the distance, d_i, between node i and node $i+1$, $P_{tx}(i, i+1)$ can be replaced with $P_{tx}(d_i)$. Hence,

$$E_{route} = \frac{R}{B} \cdot t \cdot (\sum_{i=1}^{m} P_{tx}(d_i) + m \cdot P_{rx}) + [(m+1) - 2 \cdot m \cdot \frac{R}{B}] \cdot t \cdot P_{idle}. \tag{14}$$

Assuming a $1/d^n$ path loss, $P_{tx}(d)$ can be modeled as $P_{tx}(d) = P_{base} + \alpha_2 \cdot d^n$, where $\alpha_2 \cdot d^n$ represents the transmit power level, $P_t(i, j)$, and α_2 accounts for the power to drive the transmitter amplifier [16]. Without loss of generality, we assume a uniform transmission range, D. However, the analysis of characteristic hop count can easily be extended to the non-uniform case. Since E_{route} is convex, it is minimized when all hop distances are equal. Therefore, using $d_i = D/m$,

$$E_{route} = \frac{R}{B} \cdot t \cdot m \cdot (P_{tx}(D/m) + P_{rx}) + [(m+1) - 2 \cdot m \cdot \frac{R}{B}] \cdot t \cdot P_{idle}. \tag{15}$$

To find the hop count that minimizes E_{route}, m_{opt}, we solve $\frac{\partial E_{route}}{\partial m} = 0$, which results in:

$$m_{opt} = \sqrt[n]{\frac{(n-1) \cdot \alpha_2}{P_{base} + P_{rx} + \frac{1-2(R/B)}{R/B} \cdot P_{idle}}} \cdot D. \tag{16}$$

Since the characteristic hop count is an integral value, it is $\lceil m_{opt} \rceil$ if $m_{opt} < 1$, and $\lfloor m_{opt} \rfloor$ if $m_{opt} \geq 1$.

By definition, relay-based communication saves energy if the characteristic hop count satisfies $\lfloor m_{opt} \rfloor \geq 2$. Therefore, we plot m_{opt} for four current wireless cards as R/B increases (see Fig. 7). The radio model

for each wireless card is given in Table 1. We use the existing models for Cabletron [20] and the first order radio model, denoted as LEACH, proposed in [21]. The transmission power models for Aironet 350 and Mica2 [19] are derived using polynomial curve fitting on existing measurement studies (see Fig. 5 and Fig. 6). In Fig. 7, since $m_{opt} < 2$ for all rates, only direct transmission achieves optimal energy savings for current cards. The case when the bandwidth is fully utilized (i.e., $R/B = 0.5$) corresponds to the case when P_{idle} has no effect. Therefore, even when the nodes can wake-up neighbors at the exact required time (i.e., when there is no idling), current cards do not save energy through relay-based communication.

Power control as an optimization metric is meaningful only for cards with certain characteristics. For instance, setting α_2 high, such as $\alpha_2 \geq 5.16 \cdot 10^{-6}$, for Cabletron satisfies $m_{opt} \geq 2$ for $R/B = 0.25$ (see Hypothetical Cabletron in Fig. 7). Consequently, the transmit power to reach the same transmission range, $D = 250m$ also increases up to $20W$. However, this transmission range cannot be supported due to transmit power limits of $1W$ by the FCC for the USA [22], and $100mW$ by ETSI for Europe [23]. Given these limitations, we are not aware of any wireless card that satisfies $m_{opt} \geq 2$. Furthermore, new wireless radios consume less energy in transmit mode than receive mode [24], which makes using relays between two nodes in transmission range even more questionable. Nevertheless, in Section 5, we also evaluate the Hypothetical Cabletron card to provide a thorough study of the trade-offs between power control and power management.

In this section, we have shown that energy-aware routing protocols that introduce additional relays between a source and a destination (like PARO [8]) actually use more energy when the energy characteristics of the radios are ignored. Unlike previous work that considers overhead from collisions and overhearing as a disadvantage to utilizing intermediate hops [25], our results indicate that multi-relay communication is not beneficial even in ideal channel conditions. It must be noted that direct long links, which are more favorable in terms of energy use, are used as long as they provide some reliability and otherwise, multi-hop routes might need to be discovered. Furthermore, we have evaluated power control only from an energy perspective and not considered its impact on spatial reuse. While power control improves spatial reuse, especially when the communication in the network consists mostly of one-hop flows, its advantage in the presence of multi-hop flows is not obvious. We will study the trade-off between energy and spatial reuse due to relay-based communication as future work.

5.2 Simulation Study

The goal of our performance evaluation is to understand the effectiveness of the heuristic approaches for energy-efficient network design. We use delivery ratio to measure communication performance, which is the ratio of the number of received data packets to the number of sent data packets. The performance in terms of energy is evaluated by energy goodput, which is the ratio of total application bits delivered to the total energy consumed (i.e., $E_{network}$).

We use ns2 [26] for our simulations. In Sections 5.2.1 and 5.2.2, we present results with the Cabletron [3] card (see Table 1). We simulate the following protocols: proactive joint optimization (DSDVH-ODPM), reactive joint optimization with and without traffic rate information (DSRH-ODPM(rate) and DSRH-ODPM(norate), respectively), and the two-stage approaches with DSR and TITAN (DSR-ODPM-PC and TITAN-PC). As indicated in the labels, the underlying power management protocol is ODPM, which uses IEEE-802.11 PSM for sleep scheduling. (We omit the pure PSM results, where all protocols show poor performance since PSM limits network capacity as traffic load increases.) For PSM, the beacon interval is 0.3s and the ATIM window is 0.02s, as suggested in [3]. Both the beacon and the ATIM intervals are long enough to compensate for the cost of switching between sleep and idle states. For ODPM, the keep-alive timers are set to 10s for RREPs and 5s for data messages.

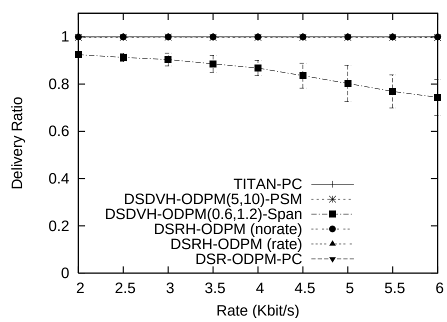

Figure 8: Delivery ratio for 500×500 network.

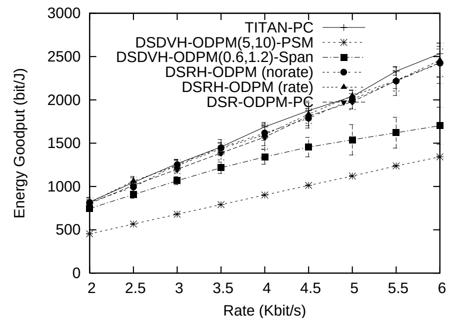

Figure 9: Energy goodput for 500×500 network.

Section 5.2.3 presents results with the Hypothetical Cabletron card, described in Section 4.1. The goal of this study is to understand the performance of power control as a primary optimization technique. We simulate two flavors of MTPR: MTPR and MTPR+. While MTPR uses transmit power level as the routing metric, MTPR+ also takes base transmit and receive power costs into account.

For both cards, transmit power levels are assumed to be infinitely adjustable. Although a continuous transmit power control model (instead of discrete transmit power levels) is optimistic, it permits us to concentrate on the trade-offs in energy-efficient network design.

5.2.1 Static Networks

In the first set of simulations, static networks with different network sizes and node densities are studied to understand pure protocol performance without mobility.

Small Networks In these simulations, 50 nodes are placed, uniformly at random, in a $500m \times 500m$ static network. There are 10 CBR flows. The start time for each flow is determined randomly between 20s and 25s. Each simulation runs for 900s. Each graph depicts an average of 5 runs and 95% confidence intervals. Similar performance trends are observed with traffic demands based on exponentially distributed inter-arrival times, which are not presented for brevity.

To understand the impact of traffic load, we evaluate performance as the traffic rate of each flow increases. The energy goodput performance of all approaches except DSDVH-ODPM is similar (see Fig. 9). Essentially, idling energy is the dominating factor since data communication consumes a small percentage of a node's energy. Since all approaches except DSDVH-ODPM use approximately the same number of nodes for communication ($\approx$ 26 nodes), their energy goodput performance is similar in a small network.

Due to periodic and triggered routing table updates, DSDVH-ODPM performs significantly worse in terms of energy goodput (e.g., $\approx$ 85% lower compared to TITAN-PC). Furthermore, since the sleep scheduling mechanism is IEEE 802.11 PSM, these updates keep all nodes awake for an entire beacon interval, increasing idling energy consumption. To reduce this adverse effect of routing table updates, we evaluate the following improvements for IEEE 802.11 PSM [3]: (1) individually advertising each broadcast message and (2) using an advertised traffic window so that a node can sleep after it receives all advertised messages. Additionally, we reduce the keep-alive timer for data packets to 0.6s (i.e., two beacon intervals) and RREPs to 1.2s. This version of DSDVH-ODPM is labeled DSDVH-ODPM(0.6,1.2)-Span in Figs. 8 and 9. As expected, the energy goodput of DSDVH-ODPM improves with these parameters (e.g., now only 10%-49%

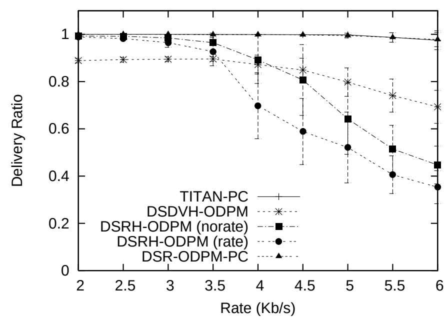

Figure 10: Delivery ratio for 1300x1300 network.

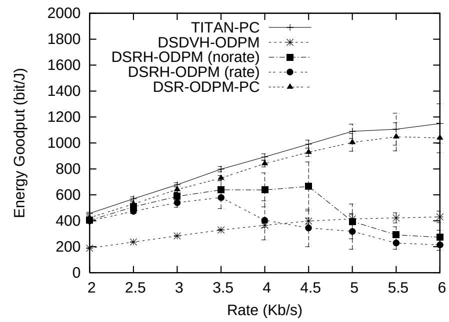

Figure 11: Energy goodput for 1300x1300 network.

Table 2: Performance as node density increases

# of nodes	DSR-ODPM-PC	TITAN-PC
Delivery Ratio		
300	0.933 ± 0.056	0.993 ± 0.004
400	0.405 ± 0.093	0.922 ± 0.102
Energy Goodput (bit/J)		
300	429.600 ± 210.264	654.294 ± 55.216
400	79.420 ± 31.776	763.700 ± 443.013

worse than TITAN-PC). However, since the advertised traffic window limits the amount of traffic updates that can be sent, the delivery ratio of DSDVH-ODPM(0.6,1.2)-Span is 74%-92%, while the rest perform with 100% delivery ratio (see Fig. 8).

These results show that the extra overhead for route discovery in joint optimization approaches is not worth its cost even in small networks. Essentially, the energy savings obtained are minimal in comparison to the two-stage protocols even if the energy cost of routing is ignored.

Large Networks To evaluate the scalability of the protocols, we next present simulation results in larger networks. We simulate 200 nodes placed uniformly at random, in a $1300m \times 1300m$ static network. There are 20 CBR flows. The start time for each flow is determined randomly between 20s and 25s. Each simulation runs for 600s. Each graph depicts an average of 10 runs and 95% confidence intervals.

In contrast to small networks, the differences in communication and energy conservation of the different approaches are now evident (see Figs. 10 and 11). First, the performance of the two-stage protocols, DSR-ODPM-PC and TITAN-PC are comparable. Second, The two-stage protocols perform significantly better than joint optimization protocols. There is a threshold per-flow rate, 3.5Kb/s, where the performance of the joint optimization protocols starts degrading and shows high deviation. Essentially, as the rate increases, the control overhead of joint optimization protocols, proactive or reactive, starts interfering with data communication.

The evaluations up to this point show that DSR-ODPM-PC and TITAN-PC perform similarly. Therefore, we further evaluate these two protocols in a 1300x1300 network with different node densities, setting the per-flow traffic rate to 4Kb/s and without changing the positions of source and destination nodes. Essentially, routing overhead of DSR-ODPM-PC explodes with network density, and therefore, limits the time a node

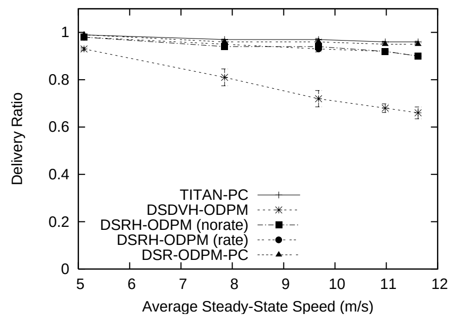

Figure 12: Delivery ratio as mobility increases.

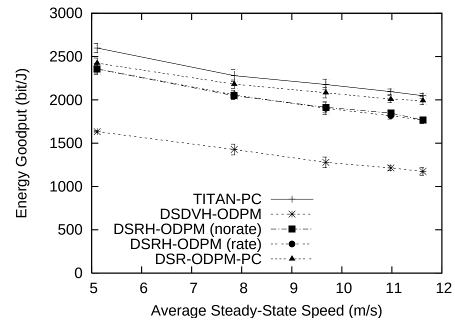

Figure 13: Energy goodput as mobility increases.

can sleep. Since, in TITAN, the already active nodes dominate route discovery, TITAN-PC can scale to denser networks in comparison to DSR-ODPM-PC (see Table 2).

These results show that two-stage approaches outperform joint optimization approaches in terms of scalability. Furthermore, as the network density increases, TITAN-PC is the only protocol that can maintain high network performance.

5.2.2 Mobile Networks

An important characteristic of ad hoc networks is the mobility of nodes, which determines how fast the link characteristics change. In this section, our goal is to evaluate how necessary it is to adapt to such dynamics to provide energy conservation. In these simulations, 50 nodes are distributed uniformly at random in a $600m \times 600m$ network. There are 10 source and destination pairs. The traffic is CBR, and the start time for each flow is determined randomly between 20s and 25s. Each graph represents an average of five runs.

We use the extended random waypoint mobility model [27]. To evaluate the impact of increasing mobility, we simulate node speed uniformly distributed between x-19m/s, where x is 1, 5, 10, 18. The pause times are uniformly distributed between 0-20s. Each run is 900s, which results in steady-state average speeds of 5.11m/s, 7.85m/s, 9.68m/s, 10.98m/s and 11.63m/s.

Simulation results show that as the mobility rates increase, DSDVH-ODPM is infeasible since it cannot keep up with the changes in the topology (see Fig. 12). Essentially, in the presence of mobility, a proactive protocol spends a large capacity of the network and the energy of nodes for exchanging routing table information. As expected, the two-stage approaches achieve the best delivery ratio and energy goodput performance since they are less susceptible to link cost changes compared to joint optimization approaches. Furthermore, since route discoveries are triggered more often due to frequent route changes, the overhead from route discovery reduces the energy goodput for the joint optimization approaches (see Fig. 13).

5.2.3 Hypothetical Networks

In this section, we evaluate all protocols with the Hypothetical Cabletron card, which provides energy savings from relay-based communication when the bandwidth utilization hits 25%. The goal of our study is to understand the trade-offs between all three heuristics when power control as a primary optimization technique is also feasible. For the sake of clarity of graphs, we omit the results for DSR-PC and DSRH(rate). DSR-PC performs worse than TITAN-PC but with similar trends, whereas DSRH(rate) is comparable to DSRH(norate).

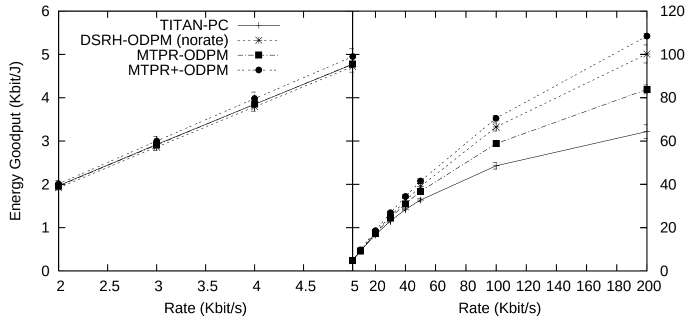

Figure 14: Energy goodput with perfect sleep scheduling.

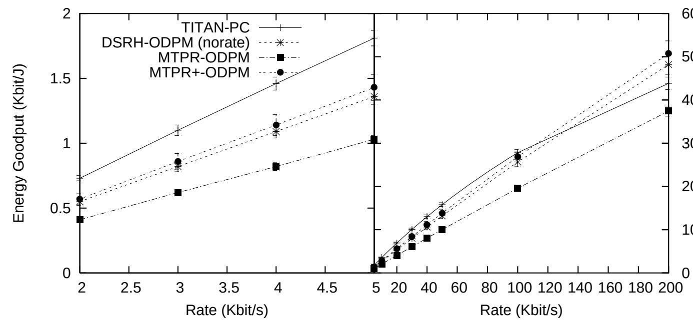

Figure 15: Energy goodput with ODPM-like scheduling.

To allow all protocols to exhibit their characteristic behavior (e.g., MTPR favors short hops and TITAN focuses traffic on single nodes), we simulate a grid topology, where nodes are closely spaced. Specifically, 49 nodes are placed on a 7×7 grid, in a $300m \times 300m$ static network. There are 7 CBR flows, where a source on the left side sends to a destination on the right side. The start time for each flow is determined randomly between 20s and 25s. Each simulation is 900s.

To understand when link cost as a routing metric pays off, we simulate per-flow traffic rates between 2K-200K (above 200K is beyond node capacity). To understand the potential of each approach without the side effects of high rates (e.g., packet losses due to buffer overflows or contention), we find the time when the routes stabilize for the 2K rate and use these routes to calculate $E_{network}$ for higher rates.

Fig. 14 shows the results with perfect sleep scheduling, where nodes wake up only when they are needed. As expected, with no idling costs, TITAN-PC achieves lower energy goodput compared to other approaches. Essentially, using longer links becomes more expensive as the traffic rate increases, although it does not hurt the performance for low rates. Furthermore, since the optimal hop count is 2 with the Hypothetical Cabletron, MTPR, which finds longer routes, performs worse than MTPR+. Fig. 15 shows the energy goodput when active nodes are always idling in the expectation of traffic, while the rest of the nodes are in sleep (like in ODPM). In this case, TITAN-PC performs better, and MTPR+ and DSRH(norate) take over only at 200Kb/s. Furthermore, the difference in performance at 200K is less pronounced compared to Fig. 14.

These results show that even with a hypothetical card and ideal scenarios, power control as a primary optimization and joint optimization provide high energy savings only with perfect sleep scheduling. When idling costs are taken into account, these approaches outperform the two-stage approach for only very high bandwidth utilization. However, it is not even clear if such high flow rates can be supported in multi-hop

wireless networks due to potentially high contention and delay. While the performance of the two-stage approach degrades with high rates for perfect sleep scheduling, higher or comparable energy savings are achieved with more realistic sleep scheduling. Therefore, our two-stage approach will remain valuable unless the characteristics of wireless cards change and perfect sleep scheduling becomes more feasible.

6 Conclusion

To save energy from wireless communication, an energy-efficient network design needs to reduce energy consumption for all radio states. In this paper, we explore the complex interactions between techniques that minimize energy consumption in each radio state and study three heuristic approaches. Evaluation results show that a two-stage approach that gives priority to idle-time energy consumption achieves the desired property of being both bandwidth and energy-efficient. Furthermore, our study exposes a commonly held myth about the potential energy savings from power control as a primary energy conservation technique.

In this work, we mainly consider minimizing instantaneous network energy consumption, which does not necessarily translate into longer network lifetime. The lifetime of a wireless network is dependent on many factors such as the type of application, network traffic, number of nodes, available energy, path loss and radio energy parameters [16]. Due to the complexity of energy-efficient network design, incorporating such lifetime constraints defined by the application is part of our future work. Additionally, we have not considered the congestion and contention effects from limiting the number of relay nodes. Furthermore, TPC is considered only from an energy conservation perspective. However, short-range communication also impacts spatial reuse in the network. We believe that the two-stage approach offers the potential for both energy savings and spatial reuse from TPC. Essentially, energy savings are obtained since TPC is only used for choosing an appropriate power level between two relays without affecting the number of relays, which also allows spatial reuse for one-hop flows. Nevertheless, we leave the study of such congestion and spatial reuse effects on routing and energy conservation as future work.

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