Traffic-oblivious Energy-aware Routing for Multihop Wireless Networks

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***Abstract*— Energy efficiency is an important issue in multihop wireless networks with energy concerns. Usually it is achieved with accurate knowledge of the traffic pattern and/or the current network information such as load and remaining energy level (in an energy constrained case). However, accurate estimation of the traffic pattern is hard to obtain. Transmission interference and lossy links exacerbate the problem.**

We have investigated the problem of designing a routing scheme to minimize the maximum energy utilization of a multihop wireless network with no or weak assumption of the traffic pattern and without ongoing collection of network information. We have developed polynomial size LP models to design such a traffic-oblivious energy-aware routing scheme, in scenarios where 1) there is no interference and links are lossless, and 2) interference is present and links are lossy. The experimental results show that the oblivious routing achieves the performance close to what an oracle can achieve. The results for multihop wireless networks with a single sink are especially good.

I. Introduction

Research in multihop wireless networks, such as wireless ad hoc networks, wireless sensor networks, wireless community mesh networks and base-stations connected by wireless links, has drawn much attention recently. Energy efficiency is a paramount issue when the energy source is costly or there are energy constraints [9]. In some wireless systems, it is critical to control heat generation, thus energy efficiency is a key factor. In a multihop wireless network with a single sink, nodes close to the sink tend to be heavily loaded. It is thus more important to balance the load in the network.

Previous work on energy efficiency has made great progress. Singh et al. [26] investigate power-aware routing in wireless ad hoc network. They propose several routing metrics and study their performance through simulation. The problem of maximizing the lifetime of a multihop wireless network with energy constraints is studied in [8], [16], [25], where the lifetime is defined as the length of the time until the first node drains out its energy. It assumes every node is important. Kar et al. [13] investigate how to route the maximal number of messages in wireless ad hoc networks with energy constraints. Sadagopan and Krishnamachari [24] study the problem of maximizing data extraction in wireless sensor networks with energy constraints. If the power supply is renewable, it is desirable that the energy consumption rate is less than the renewal rate. Lin et al. [18] study power-aware routing with renewable energy sources.

Some previous work assumes exact prior knowledge of traffic pattern, e.g. [8], [24], [25]. The traffic pattern may be known a priori in some applications, such as in a wireless sensor network in which sensors periodically report weather information. With knowledge of the traffic pattern, network flow [2] can be used to model the energy efficiency problem. Chang et al. [8] model the problem of lifetime maximization as a linear program (LP) and give a heuristic solution. Sadagopan and Krishnamachari [24] develop an approximate algorithm and a heuristic algorithm based on a LP formulation of the data extraction problem. In our work we study the optimal routing in the *minimax* sense, i.e., to minimize the maximum of the energy utilization, in multihop wireless networks. Given the traffic pattern, we can model the problem to minimax energy utilization as a LP optimization problem.

For some classes of applications, e.g. wireless community mesh networks or base stations connected by wireless links, the traffic pattern may not be known a priori. It is difficult to obtain an accurate estimate of the traffic pattern even in the scenario of the Internet [7], [28], [4], where a large amount of measurement data is available. It is likely to be difficult to estimate the traffic pattern accurately in some multihop wireless networks, e.g., in a wireless community mesh network. Recently researchers study traffic characterization in wireless networks (without energy concerns), mainly in a wireless LAN environment such as on a campus or in a corporation, e.g. Meng et al. [19]. Even if an estimate is accurate, it is in a statistical sense, which means there is an error margin with the estimation. Some wireless networks may be designed with the expected traffic pattern in mind. However, in some cases, there are unexpected or unscheduled events. In the sensor network example, where weather information is reported periodically, the sensors may also need to report temperature changes exceeding a certain threshold, which may not be predictable. Furthermore, the actual traffic may deviate from the expectation. Therefore, it is desirable to allow for errors, deviation and uncertainties in traffic prediction when designing a routing scheme. Two approaches may achieve this, namely, adaptive and oblivious.

A routing scheme may be adaptive to the traffic pattern and the network condition such as the remaining energy level in an energy-constrained case. Some adaptive approaches can bound the performance, e.g. [16], [13], [18]. They need to periodically collect information such as the current network load and the current energy level. The approach in [16] needs a regular traffic pattern to achieve the performance guarantee. The adaptive approaches in [13], [18], which are based on the work of adaptive routing in a wired network [22], have performance guarantees in the order of logarithmic to network size. It is desirable to design an efficient scheme to collect necessary information for energy efficiency with respect to both computing an energy-efficient route and economizing energy for information collection. We take an alternative approach to investigate feasibility and performance of a routing scheme oblivious to the traffic pattern and network information.

The research on oblivious routing in optimizing link utilization [23], [5], [4] has made great achievements. The oblivious routing problem is to design a routing that achieves close to the optimal performance, with no or only approximate knowledge of the traffic pattern, without considering the current network load. Räcke [23] investigates oblivious routing on general symmetric networks. Azar et al. [5] show that an optimal oblivious routing can be computed by an LP with a polynomial number of variables, but infinite number of constraints. Applegate and Cohen [4] design a simple polynomial size LP to obtain traffic-oblivious routing schemes to minimax link utilization that achieve good performance in the scenario of the Internet.

A wireless network has unique features, such as interference and dynamic channel conditions, in contrast to a wired network. Schedulability of a routing is studied in Hajek and Sasaki [10], Kodialam and Nandagopal [14] and Jain et al. [12], etc. On the other hand, emerging technologies, e.g. the ultra wideband (UWB) system [20], may create an "interference-free" wireless environment which renders schedulability of a routing no longer a (serious) problem.

Quality of service (QoS) is an important issue, especially in a wireless network with interference and time-varying channel conditions. Applications may have various QoS requirements, such as reliable transmission.

In this paper, we study a traffic-oblivious energy-aware routing scheme for multihop wireless networks. We also study its performance. We focus on wireless networks with stationary topology. Our work is applicable to low mobility. Our goal is to design a routing scheme that achieves minimax energy utilization in a multihop wireless network, with a weak assumption of the traffic pattern, without ongoing collection of network information. We develop polynomial size LP models to design such a routing scheme. The routing is fixed[1], thus it is oblivious to changes and uncertainties of the traffic. It is also oblivious to the current state of the network, such as the current energy level of wireless nodes and the current network load. It does not need to collect network information except for the stationary topology and the initial energy level. The routing achieves minimax energy utilization. Thus it is energy-aware. The routing scheme considers interference and loss when necessary. It achieves energy efficiency nearly optimally as shown in the experimental results. In contrast to the logarithmic performance guarantee of adaptive approaches [13], [18], our LP models give low, constant performance guarantee in the studied cases.

[1]The routing is "fixed" in the sense that there is a single output of the LP model. The routing can be implemented in an opportunistic way, which has the potential to combat with the fluctuation of wireless channel.

The LP models are general enough for several radio transmission models, such as omni-directional and directional antennas and a radio equipped with various possible granularities of transmission power levels. It can also work with a multi-channel and/or multi-radio wireless system.

Our major contribution is: we design a routing scheme which is energy-efficient, is independent of the traffic pattern, does not need ongoing network information collection, guarantees schedulability in an interference-limited scenario, and provides reliable transmission in a lossy environment. The experiments show that the oblivious routing can achieve the performance close to what an oracle can achieve.

The paper is organized as follows. Section II presents the network model, notation, and performance metrics. In Section III, we give linear constraints to express flow conservation, link capacity, schedulability and lossy links. In Section IV, we develop LP models to compute the optimal oblivious routing. We discuss generalization to various radio transmission models in Section IV-E and implementation issues in Section IV-F. We present the experimental results in Section V. Then we draw conclusions.

II. Model

Network Model. A multihop wireless network can be abstracted as a digraph $G = (V, E)$, where V is the set of wireless nodes and E is the set of "edges". There is an edge (u, v) if node u can reach node v. We assume the digraph is strongly connected. Each node u has an initial energy level $pow(u)$. We assume stationary channel conditions, e.g. an additive white Gaussian noise (AWGN) channel with constant noise power. We assume a transmitting node uses a fixed modulation scheme. We denote the set of neighbors of a node u as $nbr(u)$, i.e., $nbr(u) = \{v|(u, v) \in E\}$. For a neighbor v of u, we define $nbr(v, -u) = \{w|w \in nbr(v), w \neq u\}$. That is, $nbr(v, -u)$ denotes the set of neighbors of node v, a neighbor of node u, excluding node u.

Energy Consumption Model. The energy consumption to transmit a unit amount of data from a node u to another node v is $tx(u, v)$. Usually $tx(u, v)$ depends on the distance between u and v. The amount of energy consumption in transmission is proportional to the amount of data to be transmitted. This linear model is used in previous work on energy efficiency, e.g. [8], [11], [13], [16], [24], [25].

We use $r(u)$ and $h(u)$ to model the energy consumption of node u to receive and to overhear a unit of message respectively. Overhearing means receiving a packet by a node not addressed to it. We separate reception and overhearing since they may consume different amounts of energy. For instance, a node may overhear the whole data packet or only the preamble before discarding it. In the former case, overhearing consumes comparable amount of energy as reception; while in the latter overhearing may consumes much less energy. During the formulation of the LP models, we only need the function forms of these energy consumption models. In the simulation study, we will use specific models. The energy consumption for processing data may be a component of the transmission model and the reception model, thus we do not model it explicitly.

Traffic Matrix. We keep the notation *traffic matrix* (TM) as in the literature of the Internet traffic engineering, e.g. [28], [4]. Denoting the number of nodes as n, a traffic matrix is an $n \times n$ nonnegative matrix where the diagonal entries are 0. A traffic matrix provides the amount of traffic between each Origin-Destination (OD) pair over a certain time interval. It characterizes the traffic pattern in an average sense.

Maximum Energy Utilization. We introduce a performance metric, *maximum energy utilization*; and based on it, we model the energy efficiency problem as a LP optimization problem. The definition of this metric is inspired by the derivation of the maximum lifetime, e.g. in [8] and the definition of the maximum link utilization, e.g. in [4]. With this metric, we can handle more problems besides lifetime maximization.

A *routing* **f** specifies what fraction of the traffic for each OD pair is routed on each edge. We will give its detailed definition later. For a given routing **f**, a given traffic matrix $\mathbf{tm}$, the maximum energy utilization (MEU) measures the "goodness" of the routing. The lower the maximum energy utilization, the better the routing.

$$\text{MEU}(\mathbf{tm}, \mathbf{f}) = \max_s \frac{\mathbf{energy}_s}{pow(s)},$$

where $\mathbf{energy}_s$ denotes the total energy consumption for all the traffic transmitted, received and overheard by node s. We will develop its detailed expression later. Recall $pow(s)$ denote the initial energy level of s.

Minimax Energy Utilization. For a given traffic matrix $\mathbf{tm}$, the *optimal routing* minimizes the maximum energy utilization:

$$\text{OPTE}(\mathbf{tm}) = \min_{\mathbf{f}:\mathbf{f} \text{ is a routing}} \text{MEU}(\mathbf{tm}, \mathbf{f})$$

The minimax energy utilization measures the energy consumption rate of a wireless network. It can be regarded as a unification of several studied problems: lifetime maximization with or without energy renewal, maximization of the number of messages or data extraction, and minimization of power consumption. The lifetime of a wireless network is inversely proportional to the energy consumption rate of the node that consumes energy the fastest. For a given traffic matrix, once we minimax the energy utilization, we effectively maximize the lifetime of the multihop wireless network. The problem of minimizing the renewal rate can be dealt with similarly. To minimax energy utilization is equivalent with maximizing data extraction according to the data rates of the sources, which is a concurrent multicommodity problem [2]. When wireless nodes have the same initial power reserve, to minimax energy utilization is equivalent to the problem of minimizing power consumption.

Given a traffic matrix, the optimal routing to minimax energy utilization is solvable as a LP multi-commodity flow problem [2]. For now, we do not consider interference and loss. We discuss schedulability of a routing in Section III-D and concerns about loss in Section III-E. The LP to find the optimal routing is:

$$\begin{array}{l} \min p \\ \mathbf{f} \text{ is a routing} \\ \forall \text{ nodes } s : \mathbf{energy}_s / pow(s) \le p \end{array} \qquad (1)$$

LP (1) minimizes the maximum energy utilization for a given traffic matrix, i.e., LP (1) is equivalent to $\min_{\mathbf{f}} \text{MEU}(\mathbf{tm}, \mathbf{f})$. This LP is similar to that by Chang et al. [8] for maximizing the lifetime of a wireless ad hoc network.

For an application with prior knowledge of traffic pattern, the above LP model is sufficient to compute the optimal routing to minimax energy utilization. For example, it maximizes the lifetime of a wireless sensor network with periodical reports of weather information. Based on the LP model, efficient and/or distributed algorithms can be developed.

Competitive Ratio. The routing computed by LP (1) does not guarantee performance for other traffic matrices. We will develop LP models to compute the optimal routing that achieves minimax energy utilization with a weak assumption on the traffic pattern. First we introduce the metric of competitive ratio that follows the competitive analysis [22], [4].

For a given routing **f**, a given traffic matrix **tm**, the *competitive ratio* is defined as the ratio of the maximum energy utilization of the routing **f** on the traffic matrix **tm** to the maximum energy utilization of the optimal routing. Competitive ratio measures how far the routing **f** is from the optimal routing on the traffic matrix **tm**. Formally,

$$\text{CR}(\mathbf{f}, \{\mathbf{tm}\}) = \frac{\text{MEU}(\mathbf{tm}, \mathbf{f})}{\text{OPTE}(\mathbf{tm})}$$

The competitive ratio is usually greater than 1. It is equal to 1 only when the routing **f** is an optimal routing.

When we are considering a set of traffic matrices **TM**, the competitive ratio of a routing **f** is defined as

$$\text{CR}(\mathbf{f}, \mathbf{TM}) = \max_{\mathbf{tm} \in \mathbf{TM}} \text{CR}(\mathbf{f}, \mathbf{tm})$$

The competitive ratio with respect to a set of traffic matrices is usually strictly greater than 1, since a single routing can't optimize energy utilization over the set of traffic matrices.

When set **TM** includes all possible traffic matrices, $\text{CR}(\mathbf{f}, \mathbf{TM})$ is referred to as the *oblivious competitive ratio* of the routing **f**. This is the worse competitive ratio the routing **f** achieves with respect to all traffic matrices. An *optimal oblivious routing* is the routing that minimizes the oblivious competitive ratio. Its oblivious ratio is the *optimal oblivious ratio* of the network.

Suppose there is an oracle that knows the instant traffic matrix **tm** and computes its optimal routing with energy utilization e. The energy utilization of the optimal oblivious routing for **tm** is guaranteed to be within $[e, r * e]$, where r is the oblivious ratio. It may achieve lower energy utilization than $r * e$ for the particular traffic matrix **tm**. The oblivious routing guarantees the oblivious ratio for all traffic matrices. That is, the oblivious routing guarantees a performance with the ratio to the performance of the oracle.

III. LINEAR CONSTRAINTS

Before developing the LP formulation for the routing scheme, we give linear constraints to reflect flow conservation, link capacity, schedulability and lossy links.

A. Routing **f** and Flow **g**

An entry in a traffic matrix d_{ij} denotes the amount of traffic of OD pair $i \to j$. A routing $f_{ij}(s,t)$ specifies the fraction of traffic demand d_{ij} on edge (s,t). The flow on edge (s,t) for d_{ij} is $d_{ij} f_{ij}(s,t)$, i.e., $g_{ij}(s,t) = d_{ij} f_{ij}(s,t)$. Both a routing and a flow will follow the conservation constraint.

Routing **f** is defined as:

$$\begin{cases} \forall \text{ pairs } i \to j : \sum\limits_{(i,u) \in out(i)} f_{ij}(i,u) = 1 \\ \forall \text{ pairs } i \to j, \forall \text{ nodes } k \neq i,j : \\ \quad \sum\limits_{(k,u) \in out(k)} f_{ij}(k,u) - \sum\limits_{(v,k) \in in(k)} f_{ij}(v,k) = 0 \\ \forall \text{ pairs } i \to j, \forall \text{ edges } (s,t) : f_{ij}(s,t) \geq 0 \end{cases} \tag{2}$$

Flow **g** is defined as,

$$\begin{cases} \forall \text{ pairs } i \to j, k \neq i,j : \\ \quad \sum\limits_{(k,u) \in out(k)} g_{ij}(k,u) - \sum\limits_{(v,k) \in in(k)} g_{ij}(v,k) = 0 \\ \forall \text{ pairs } i \to j : \sum\limits_{(t,j) \in in(j)} g_{ij}(t,j) - d_{ij} = 0 \\ \forall \text{ pairs } i \to j, \forall \text{ edges } (u,v) : g_{ij}(u,v) \geq 0 \\ \forall \text{ pairs } i \to j : d_{ij} \geq 0 \end{cases} \tag{3}$$

As will be clear later, we can simplify LP formulations by collapsing flows g_{ij} on an edge $u \to v$ with the same origin by $g_i(u,v) = \sum_j g_{ij}(u,v)$.

B. Link Capacity Constraint

Link capacity constraint stipulates that the flow on a link can not exceed the link capacity. Denote the capacity of link (s,t) as $c(s,t)$. We have:

$$\forall \text{ links } (s,t) : \sum_{i,j} g_{ij}(s,t) \leq c(s,t) \tag{4}$$

C. Energy Consumption

The energy consumption of node s for d_{ij} is,

$$\begin{aligned} \text{energy}_s(i,j) = & \sum_{t: t \in nbr(s)} \{g_{ij}(s,t) tx(s,t)\} \\ & + \sum_{t: s \in nbr(t)} \{g_{ij}(t,s) r(s)\} \\ & + \sum_{t: s \in nbr(t)} \sum_{k: k \in nbr(t,-s)} \{I_{(t,s)}^{(t,k)} g_{ij}(t,k) h(s)\} \end{aligned} \tag{5}$$

$I_{(t,s)}^{(t,k)}$ is an indicator function defined as,

$$I_{(t,s)}^{(t,k)} = \begin{cases} 1 & \text{if } s \text{ can overhear transmission from } t \text{ to } k; \\ 0 & \text{otherwise.} \end{cases}$$

The first term in $\text{energy}_s(i)$ is the energy consumption for transmission; the second for reception and the third for overhearing. We use $I_{(t,s)}^{(t,k)}$ to indicate that if node s is within the transmission range of the transmission from t to k, s can overhear the transmission and consumes energy for the overhearing. Chang et. al. consider only the energy consumption for transmission [8]. Further investigation consider energy consumption for both transmission and reception [24]. We also consider the energy consumption for overhearing.

The total energy consumption for node s is,

$$\mathbf{energy}_s = \sum_{i,j} \text{energy}_s(i,j).$$

D. Schedulability

In an interference-limited wireless network, it is necessary to consider schedulability of a routing. To optimize a schedulable routing is essentially to solve an optimization problem at the intersection of the feasible flow space and the feasible schedule space. The problem of scheduling with interference is NP-hard itself. Thus researchers seek necessary and sufficient condition for a flow to be schedulable. In the problem to maximize network flow (throughput), researchers look for lower and upper bounds for the schedulable flow. We discuss how to guarantee schedulability of an oblivious routing.

The free of secondary interference model [6] receives considerable attention. Hajek and Sasaki [10] investigate the schedulability of a routing in polynomial time. Kodialam and Nandagopal [14] give necessary and sufficient conditions implicitly in [10]. These conditions are expressed as linear constraints over the flows and data rate on neighboring edges of a node. For the case of multihop wireless networks with a single sink, in terms of our notation, the necessary and sufficient conditions can be expressed as follows for each node s when β takes the values of 1 and $\frac{2}{3}$ respectively:

$$\forall \text{ nodes } s, \sum_{t: t \in nbr(s)} \sum_{i,j} \frac{g_{ij}(s,t)}{c(s,t)} + \sum_{t: s \in nbr(t)} \sum_{i,j} \frac{g_{ij}(t,s)}{c(t,s)} \leq \beta. \tag{6}$$

Recall $c(s,t)$ denotes the capacity of link (s,t). The sufficient condition with $\beta = \frac{2}{3}$ guarantees schedulability.

Jain et al. [12] introduce conflict graph to model interference relationship between links. In the conflict graph, a vertex represents a link in the connectivity graph. There is an edge between two vertices in the conflict graph, if the two corresponding links in the connectivity graph interfere with each other. They consider two interference models. In the protocol interference model, a transmission is successful if the receiver is within the transmission range of the transmitter and any node within its interference range does not transmit. In the physical interference model, a transmission is successful if the signal-to-noise ratio (SNR) at the receiver exceeds a threshold, where SNR is determined by the ambient noise of the receiving node and the interference due to other ongoing transmissions. They study the lower and upper bounds on the achievable network flow (throughput). For the lower bound, independent sets (in which there is no edge for any two vertices) in the conflict graph are used to add constraints to the space of feasible network flows so that the resulting flow is schedulable. First find K maximum independent sets, $I_i, 1 \leq i \leq K$. Let

λ_i denote the fraction of time allocated to independent set I_i.

$$\begin{array}{l} \sum_{i=1}^{K} \lambda_i \leq 1 \\ \sum_{i,j} g_{ij}(s,t) \leq \sum_{(s,t)\in I_i} \lambda_i c(s,t) \end{array} \tag{7}$$

The first constraint requires that only one independent set can be active at a time. The second requires that the flow can not exceed the convex combination of edge capacities in the independent sets. Although it is hard to obtain all the independent sets to make the lower bound tight, the bound gets tighter with more independent sets [12].

The 802.11 protocol uses Request to Send (RTS) and Clear to Send (CTS) to establish interference-free, reliable connection between two nodes. For this interference model, the above discussion based on Jain et al. [12] is still applicable.

We can use constraints (6) or (7) or linear constraints based on new progress, e.g. Kumar et al. [15], to guarantee schedulability. On the other hand, emerging technologies, e.g. the ultra wideband (UWB) system [20], may create an "interference-free" wireless environment which renders schedulability of a routing no longer a (serious) problem. In this paper, we focus on the interference-limited scenario.

E. Lossy Links

Most previous work on energy efficiency based on a LP model, e.g., [8], [16], [24], [25] implicitly assumes the wireless links are lossless. Loss may be ignored in wired networks when formulating a LP network flow model. This may not be the case in wireless networks. A wireless link is usually lossy and some applications need reliable transmission. As a consequence, a packet may require several transmissions. Thus modifications need to be made to the usual flow conservation constraints, by considering some link loss factor, which measures the average number of transmissions needed to successfully transmit a packet on the link. We assume there is a link loss factor $\gamma_{ij} \geq 1$ for each edge (i,j). This link loss factor characterizes the quality of the transmission channel. The loss may result from multi-path fading, attenuation, etc. We will assume a synchronized slotted system in an interference-limited environment. Interference is thus not a factor for the loss. We assume a loss happens in the transmission medium. That is, after the sender transmits a packet, it may get lost or not. If the packet is lost, the receiver and the neighboring nodes can not hear it at all. If there is a *constant* link loss factor $\gamma_{ij} \geq 1$ for each edge (i,j), we have linear flow conservation constraints. In [17], we investigate the impact of loss on energy efficiency and throughput. The routing definition (2) remains the same. The definition of flow $\mathbf{g}$ in (3) becomes:

$$\begin{cases} \forall \text{ pairs } i \rightarrow j, \text{ nodes } k \neq i \neq j: \\ \quad \sum_{(k,u)\in out(k)} \frac{g_{ij}(k,u)}{\gamma ku} - \sum_{(v,k)\in in(k)} \frac{g_{ij}(v,k)}{\gamma vk} = 0 \\ \forall \text{ pairs } i \rightarrow j: \sum_{(i,u)\in out(i)} \frac{g_{ij}(i,u)}{\gamma_{iu}} - d_{ij} = 0 \\ \forall \text{ pairs } i \rightarrow j, \forall \text{ edges } (u,v): g_{ij}(u,v) \geq 0 \\ \forall \text{ pairs } i \rightarrow j: d_{ij} \geq 0 \end{cases} \tag{8}$$

In (8), $g_{ij}(u,v)$ denotes the actual flow of OD pair $i \rightarrow j$ on edge (u,v) (due to retransmissions); while $\frac{g_{ij}(u,v)}{\gamma_{uv}}$ denotes the effective flow. We have $g_{ij}(s,t) = \gamma_{st} d_{ij} f_{ij}(s,t)$.

The energy consumption model needs to change in a lossy environment. Since $g_{ij}(u,v)$ denotes the actual flow originating for OD pair $i \rightarrow j$ on edge (u,v), there is no change for the term for transmission. For reception, node s receives one copy out of γ_{ts} transmissions from t to s. For overhearing, node s receives one copy out of γ_{ts} transmissions from t to k. Thus, with lossy links, the energy consumption of node s for d_{ij} is,

$$\begin{aligned} \text{energy}_s(i,j) = & \sum_{t:t\in nbr(s)} \{g_{ij}(s,t)tx(s,t)\} \\ & + \sum_{t:s\in nbr(t)} \{\tfrac{g_{ij}(t,s)}{\gamma_{ts}} r(s)\} \\ & + \sum_{t:s\in nbr(t)} \sum_{k:k\in nbr(t,-s)} \{I_{(t,s)}^{(t,k)} \tfrac{g_{ij}(t,k)}{\gamma_{ts}} h(s)\} \end{aligned} \tag{9}$$

Or, equivalently,

$$\begin{aligned} \text{energy}_s(i,j) = & \sum_{t:t\in nbr(s)} \{\gamma_{st} d_{ij} f_{ij}(s,t) tx(s,t)\} \\ & + \sum_{t:s\in nbr(t)} \{d_{ij} f_{ij}(t,s) r(s)\} \\ & + \sum_{t:s\in nbr(t)} \sum_{k:k\in nbr(t,-s)} \{I_{(t,s)}^{(t,k)} \tfrac{\gamma_{tk} d_{ij} f_{ij}(t,k)}{\gamma_{ts}} h(s)\} \end{aligned} \tag{10}$$

When the wireless link is lossless, its loss factor γ is 1.

IV. The Routing Scheme

We first derive the LP models for the traffic-oblivious energy-aware routing in the scenario interference is present and links are lossy. Then we give the LP formulations directly when there is no interference and links are lossless. After that, we discuss generalization and implementation issues.

A. Routing With No Knowledge of Traffic Pattern

Similar to Azar et al. [5], the optimal oblivious routing of a multihop wireless network can be obtained by solving an LP with a polynomial number of variables, but infinitely many constraints. We call this LP "master LP":

$$\begin{array}{l} \min r \\ \mathbf{f} \text{ is a routing} \\ \forall \text{ nodes } s, \forall \text{ TMs } \mathbf{tm} \text{ with OPTE}(\mathbf{tm}) = 1: \\ \quad \sum_{ij} \text{energy}_s(i,j)/pow(s) \leq r \\ \quad \text{Constraints (4) and (6)} \end{array} \tag{11}$$

We add link capacity constraint (4) and schedulability constraint (6). The oblivious ratio is invariant with the scaling of the traffic matrices or the scaling of the initial energy level. Thus, when calculating the oblivious ratio, it is sufficient to consider traffic matrices with OPT($\mathbf{tm}$) $=$ 1. Another benefit of using traffic matrices with OPT($\mathbf{tm}$) $=$ 1 is that the objective of the LP r, which is the maximum energy utilization of the oblivious routing, is just the oblivious ratio of the network.

Given a routing **f**, the constraint of the master LP (11) can be checked by solving the following "slave LP" for each node s to examine whether the objective is $\leq r$ or not.

$$\begin{array}{l} \max \sum_{i,j} \text{energy}_s(i,j)/pow(s) \\ g_{ij} \text{ is a flow of demand } d_{ij} \\ \forall \text{ nodes } u : \sum_{i,j} \text{energy}_u(i,j) \leq pow(u) \\ \text{Constraints (4) and (6)} \\ \text{OPTE}(\mathbf{tm}) = 1 \text{ equality constraint} \\ \forall \text{ pairs } i \to j : d_{ij} \geq 0 \end{array} \tag{12}$$

We put a "OPTE(**tm**) = 1 equality constraint" in LP (12). This constraint requires that, for at least one node, the node capacity inequality constraint takes the equality form. This constraint prevents that, at optimality, all the energy capacity constraints take inequality form, which violates the condition OPTE(**tm**) = 1. We will discuss how to express it as a linear constraint when we develop the dual of LP (12). The constraints of LP (12) guarantee that the traffic can be routed with maximum energy utilization of 1.

Although the above "master-slave" LPs can solve the optimal oblivious routing problem with polynomial time based on the Ellipsoid algorithm [21], it is not practical for large networks. Inspired by the work of Applegate and Cohen [4], we derive simpler LP models to compute the oblivious ratio.

We can simplify the LP formulation using $g_i(u,v) = \sum_j g_{ij}(u,v)$. We can also relax the flow conservation constraint from equality to ≤ 0, which allows for node i to deliver more flow than demanded, and does not affect the maximum energy utilization of 1. LP (12) becomes,

$$\begin{array}{l} \max \frac{1}{pow(s)}\{\sum_{i,j} \sum_{t:t\in nbr(s)} \{\gamma_{st} d_{ij} f_{ij}(s,t) tx(s,t)\} \\ \quad + \sum_{i,j} \sum_{t:s\in nbr(t)} \{d_{ij} f_{ij}(t,s) r(s)\}\} \\ \quad + \sum_{i,j} \sum_{t:s\in nbr(t)} \sum_{u:u\in nbr(t,-s)} \{I_{(t,s)}^{(t,u)} \frac{\gamma_{tu} d_{ij} f_{ij}(t,u)}{\gamma_{ts}} h(s)\}\} \\ \forall \text{ pairs } i \to j : \\ \quad \sum_{(j,v)\in out(j)} g_i(j,v) - \sum_{(u,j)\in in(j)} g_i(u,j) + d_{ij} \leq 0 \\ \forall \text{ nodes } u : \\ \quad \sum_i \sum_{v:v\in nbr(u)} \{g_i(u,v) tx(u,v)\} \\ \quad + \sum_i \sum_{v:u\in nbr(v)} \{\frac{g_i(v,u)}{\gamma_{vu}} r(u)\} \\ \quad + \sum_i \sum_{v:u\in nbr(v)} \sum_{w:w\in nbr(v,-u)} \{I_{(v,u)}^{(v,w)} \frac{g_i(v,w)}{\gamma_{vu}} h(u)\} \\ \quad \leq pow(u) \\ \forall \text{ links } (u,v) : \sum_i g_i(u,v) \leq c(u,v) \\ \forall \text{ nodes } u : \sum_{v:v\in nbr(u)} \sum_i \frac{g_i(u,v)}{c(u,v)} + \sum_{v:u\in nbr(v)} \sum_i \frac{g_i(v,u)}{c(v,u)} \leq \beta \\ \text{OPTE}(\mathbf{tm}) = 1 \text{ equality constraint} \\ \forall \text{ nodes } i, \text{ edges } (u,v) : g_i(u,v) \geq 0 \\ \forall \text{ pairs } i \to j : d_{ij} \geq 0 \end{array} \tag{13}$$

The dual of LP (13) is:

$$\begin{array}{l} \min \sum_u \{\pi_s(u) pow(u) + \sum_v \kappa_s(u,v) c(u,v) + \beta \psi_s(u)\} \\ \forall \text{ pairs } i \to j : \\ \quad p_s(i,j) \geq \sum_{t:(s,t)\in E} \{\gamma_{st} f_{ij}(s,t) tx(s,t)\}/pow(s) \\ \quad + \sum_{t:s\in nbr(t)} \{f_{ij}(t,s) r(s)\}/pow(s) \\ \quad + \sum_{t:s\in nbr(t)} \sum_{k:k\in nbr(t,-s)} \{I_{(t,s)}^{(t,k)} \frac{\gamma_{tk} f_{ij}(t,k)}{\gamma_{ts}} h(s)\}/pow(s) \\ \forall \text{ nodes } i, \forall \text{ edges } (u,v) : \\ \quad tx(u,v)\pi_s(u) + \frac{r(v)}{\gamma_{uv}} \pi_s(v) \\ \quad + \sum_{k:k\in nbr(u,-v)} \frac{h(k)}{\gamma_{uk}} \pi_s(k) \\ \quad + p_s(i,u) - p_s(i,v) + \kappa_s(u,v) + \psi_s(u) + \psi_s(v) \geq 0 \\ \sum_u \pi_s(u) > 0 \\ \forall \text{ nodes } u,v : \pi_s(u) \geq 0, \psi_s(u) \geq 0, \kappa_s(u,v) \geq 0 \\ \forall \text{ pairs } i \to j : p_s(i,j) \geq 0, p_s(i,i) = 0 \end{array} \tag{14}$$

The correspondence between dual variables and primal constraints follows: $p_s(i,j)$ corresponding to the flow conservation constraint for the demand d_{ij}; $\pi_s(u)$ corresponding to the energy constraint for node u; $\kappa_s(u,v)$ corresponding to the link capacity constraint for link (u,v); and $\psi_s(u)$ corresponding to the schedulability constraint for node u. Since there is no conservation constraint for the demand d_{ii}, we introduce $p_s(i,i) = 0$ for convenience.

We introduce the constraint $\sum_u \pi_s(u) > 0$ in the dual LP (14) to express the OPTE(**tm**) = 1 equality constraint in the primal LP (13), i.e. to guarantee the node energy inequality constraint takes the equality form for at least one node. From the complementary slackness optimality conditions [21], we know that if the dual variable corresponding to the capacity constraint in the primal LP is non-zero, the constraint is tight. That is, if the dual variable $\pi_s(u)$ is non-zero, the primal constraint for $pow(u)$ is tight (the maximum energy utilization is 1). By this way, we guarantee the condition OPTE(**tm**) = 1 in LP (13).

According to the duality theory [21], the primal LP and its dual LP have the same optimal value if they exist. That is, LP (13) and LP (14) are equivalent. Because LP (14) is a minimization problem, we can use its objective in place of the objective of LP (13) in the "$\leq r$" constraints of LP (11). Replacing the constraint in the master LP (11) with LP (14), we obtain a single LP to compute the oblivious performance ratio for a multihop wireless network.

$$
\begin{aligned}
&\min r\\
&\mathbf{f} \text{ is a routing}\\
&\forall \text{ nodes } s:\\
&\quad \sum_u \{\pi_s(u)pow(u) + \sum_v \kappa_s(u,v)c(u,v) + \beta\psi_s(u)\} \le r\\
&\quad \forall \text{ pairs } i \to j:\\
&\qquad p_s(i,j) \ge \sum_{t:(s,t)\in E} \{\gamma_{st} f_{ij}(s,t)tx(s,t)\}/pow(s)\\
&\qquad + \sum_{t:s\in nbr(t)} \{f_{ij}(t,s)r(s)\}/pow(s)\\
&\qquad + \sum_{t:s\in nbr(t)} \sum_{k:k\in nbr(t,-s)} \{I_{(t,s)}^{(t,k)} \frac{\gamma_{tk} f_{ij}(t,k)}{\gamma_{ts}} h(s)\}/pow(s)\\
&\quad \forall \text{ nodes } i, \forall \text{ edges } (u,v):\\
&\qquad tx(u,v)\pi_s(u) + \frac{r(v)}{\gamma_{uv}}\pi_s(v)\\
&\qquad + \sum_{k:k\in nbr(u,-v)} I_{(u,v)}^{(u,k)} \frac{h(k)}{\gamma_{uk}} \pi_s(k)\\
&\qquad + p_s(i,u) - p_s(i,v) + \kappa_s(u,v) + \psi_s(u) + \psi_s(v) \ge 0\\
&\quad \sum_u \pi_s(u) > 0\\
&\quad \forall \text{ nodes } u,v: \pi_s(u) \ge 0, \psi_s(u) \ge 0, \kappa_s(u,v) \ge 0\\
&\quad \forall \text{ pairs } i \to j: p_s(i,j) \ge 0, p_s(i,i) = 0
\end{aligned}
\tag{15}
$$

B. Routing with Range Restrictions on Traffic Pattern

Next we derive an LP model to compute the oblivious ratio for a multihop wireless network when approximate knowledge of traffic pattern is known. Suppose we know that the traffic demand d_{ij} is within the range $[a_{ij}, b_{ij}]$. Without the restriction OPTE(**tm**) = 1, the master LP (11) becomes:

$$
\begin{aligned}
&\min r\\
&\mathbf{f} \text{ is a routing}\\
&\forall \alpha > 0, \forall \text{ nodes } s:\\
&\quad \forall \text{ TMs } \mathbf{tm} \text{ with OPTE}(\mathbf{tm}) = \alpha, \text{ and } \forall i,j\ a_{ij} \le d_{ij} \le b_{ij}:\\
&\qquad \sum_{i,j} \text{energy}_s(i,j)/pow(s) \le r\alpha\\
&\qquad \text{Constraints (4) and (6).}
\end{aligned}
\tag{16}
$$

Since the oblivious ratio r is invariant with respect to the scaling of traffic demands, we can consider a scaled TM $\mathbf{tm}' = \alpha\mathbf{tm}$. With $\alpha = 1/\text{OPTE}(\mathbf{tm})$, we have OPTE($\mathbf{tm}'$) = 1. Under these conditions, the master LP is:

$$
\begin{aligned}
&\min r\\
&\mathbf{f} \text{ is a routing}\\
&\forall \text{ nodes } s, \forall \text{ TMs } \mathbf{tm} \text{ with } \lambda > 0 \text{ such that}:\\
&\quad \text{TMs } \mathbf{tm} \text{ with OPTE}(\mathbf{tm}) = 1 \text{ and } \lambda a_{ij} \le d_{ij} \le \lambda b_{ij}:\\
&\qquad \sum_{i,j} \text{energy}_s(i,j)/pow(s) \le r\\
&\qquad \text{Constraints (4) and (6).}
\end{aligned}
\tag{17}
$$

As in Section IV-A, we can derive the constraints that satisfy the requirement that traffic matrices can be routed with maximum energy utilization of 1. We need to add the constraint $\lambda a_{ij} \le d_{ij} \le \lambda b_{ij}$, when we know the range restriction of the traffic matrix. We still use $g_i(u,v) = \sum_j g_{ij}(u,v)$ to simplify the formulation as before. The slave LP for node s is thus,

$$
\begin{aligned}
&\max \frac{1}{pow(s)}\{\sum_{i,j} \sum_{t:t\in nbr(s)} \{\gamma_{st} d_{ij} f_{ij}(s,t)tx(s,t)\}\\
&\quad + \sum_{i,j} \sum_{t:s\in nbr(t)} \{d_{ij} f_{ij}(t,s)r(s)\}\}\\
&\quad + \sum_{i,j} \sum_{t:s\in nbr(t)} \sum_{u:u\in nbr(t,-s)} \{I_{(t,s)}^{(t,u)} \frac{\gamma_{tu} d_{ij} f_{ij}(t,u)}{\gamma_{ts}} h(s)\}\}\\
&\forall \text{ pairs } i \to j: && \Leftarrow p_s(i,j)\\
&\quad \sum_{(j,v)\in out(j)} g_i(j,v) - \sum_{(u,j)\in in(j)} g_i(u,j) + d_{ij} \le 0\\
&\forall \text{ nodes } u: && \Leftarrow \pi_s(u)\\
&\quad \sum_i \sum_{v:v\in nbr(u)} \{g_i(u,v)tx(u,v)\}\\
&\quad + \sum_i \sum_{v:u\in nbr(v)} \{\frac{g_i(v,u)}{\gamma_{vu}} r(u)\}\\
&\quad + \sum_i \sum_{v:u\in nbr(v)} \sum_{w\in nbr(v,-u)} \{I_{(v,u)}^{(v,w)} \frac{g_i(v,w)}{\gamma_{vu}} h(u)\}\\
&\quad \le pow(u)\\
&\forall \text{ links } (u,v): \sum_i g_i(u,v) \le c(u,v) && \Leftarrow \kappa_s(u,v)\\
&\forall \text{ nodes } u: && \Leftarrow \psi_s(u)\\
&\quad \sum_{v:v\in nbr(u)} \sum_i \frac{g_i(u,v)}{c(u,v)} + \sum_{v:u\in nbr(v)} \sum_i \frac{g_i(v,u)}{c(v,u)} \le \beta\\
&\text{OPTE}(\mathbf{tm}) = 1 \text{ equality constraint}\\
&\forall \text{ pairs } i \to j: d_{ij} - \lambda b_{ij} \le 0 && \Leftarrow w_s^+(i,j)\\
&\forall \text{ pairs } i \to j: -d_{ij} + \lambda a_{ij} \le 0 && \Leftarrow w_s^-(i,j)\\
&\forall \text{ nodes } i, \text{ edges } (u,v): g_i(u,v) \ge 0\\
&\forall \text{ pairs } i \to j: d_{ij} \ge 0
\end{aligned}
\tag{18}
$$

The dual of LP (18) is:

$$
\begin{aligned}
&\min \sum_u \{\pi_s(u)pow(u) + \sum_v \kappa_s(u,v)c(u,v) + \beta\psi_s(u)\}\\
&\forall \text{ pairs } i \to j: && \Leftarrow d_{ij}\\
&\quad p_s(i,j) + w_s^+(i,j) - w_s^-(i,j) \ge\\
&\quad \sum_{t:(s,t)\in E} \{\gamma_{st} f_{ij}(s,t)tx(s,t)\}/pow(s)\\
&\quad + \sum_{t:s\in nbr(t)} \{f_{ij}(t,s)r(s)\}/pow(s)\\
&\quad + \sum_{t:s\in nbr(t)} \sum_{u:u\in nbr(t,-s)} \{I_{(t,s)}^{(t,u)} \frac{\gamma_{tu} f_{ij}(t,u)}{\gamma_{ts}} h(s)\}/pow(s)\\
&\forall \text{ nodes } i, \forall \text{ edges } (u,v): && \Leftarrow g_i(u,v)\\
&\quad tx(u,v)\pi_s(u) + \frac{r(v)}{\gamma_{uv}}\pi_s(v)\\
&\quad + \sum_{k:k\in nbr(u,-v)} I_{(u,v)}^{(u,k)} \frac{h(k)}{\gamma_{uk}} \pi_s(k)\\
&\quad + p_s(i,u) - p_s(i,v) + \kappa_s(u,v) + \frac{\psi_s(u)}{c(u,v)} + \frac{\psi_s(v)}{c(v,u)} \ge 0\\
&\sum_u \pi_s(u) > 0\\
&\forall \text{ pairs } i \to j: \sum_i \{w_s^-(i,j)a_{i,j} - w_s^+(i,j)b_{i,j}\} \ge 0 && \Leftarrow \lambda\\
&\forall \text{ nodes } u,v: \pi_s(u) \ge 0, \psi_s(u) \ge 0, \kappa_s(u,v) \ge 0\\
&\forall \text{ pairs } i \to j: p_s(i,j) \ge 0, p_s(i,i) = 0
\end{aligned}
\tag{19}
$$

Comparing with LP (13), LP (18) has the extra range constraints $d_{ij} - \lambda b_{ij} \le 0$ and $-d_{ij} + \lambda a_{ij} \le 0$. Consequently LP (19) has extra dual variables $w_s^+(i,j)$ and $w_s^-(i,j)$, which are associated with the range constraints. To help make the derivation of the dual LP (19) clearer, we use leftarrow $\Leftarrow$ to indicate dual variables corresponding with primal constraints in LP (18). In dual LP (19), we indicate primal variables corresponding to dual constraints.

Thus with the approximate knowledge d_{ij} being within $[a_{ij}, b_{ij}]$, the LP to calculate the oblivious routing is:

$$
\begin{array}{l}
\min r \\
\mathbf{f} \text{ is a routing} \\
\forall \text{ nodes } s: \\
\quad \sum_u \{\pi_s(u)pow(u) + \sum_v \kappa_s(u,v)c(u,v) + \beta\psi_s(u)\} \le r \\
\quad \forall \text{ pairs } i \to j: \\
\quad\quad p_s(i,j) + w_s^+(i,j) - w_s^-(i,j) \ge \\
\quad\quad \sum_{t:(s,t)\in E} \{\gamma_{st} f_{ij}(s,t) tx(s,t)\}/pow(s) \\
\quad\quad + \sum_{t:s\in nbr(t)} \{f_{ij}(t,s)r(s)\}/pow(s) \\
\quad\quad + \sum_{t:s\in nbr(t)} \sum_{u:u\in nbr(t,-s)} \{I_{(t,s)}^{(t,u)} \frac{\gamma_{tu} f_{ij}(t,u)}{\gamma_{ts}} h(s)\}/pow(s) \\
\quad \forall \text{ nodes } i, \forall \text{ edges } (u,v): \\
\quad\quad tx(u,v)\pi_s(u) + \frac{r(v)}{\gamma_{uv}}\pi_s(v) \\
\quad\quad + \sum_{k:k\in nbr(u,-v)} I_{(u,v)}^{(u,k)} \frac{h(k)}{\gamma_{uk}} \pi_s(k) \\
\quad\quad + p_s(i,u) - p_s(i,v) + \kappa_s(u,v) + \frac{\psi_s(u)}{c(u,v)} + \frac{\psi_s(v)}{c(v,u)} \ge 0 \\
\quad \sum_u \pi_s(u) > 0 \\
\quad \forall \text{ pairs } i \to j: \\
\quad\quad \sum_i \{w_s^-(i,j)a_{i,j} - w_s^+(i,j)b_{i,j}\} \ge 0 \\
\quad \forall \text{ nodes } u,v: \pi_s(u) \ge 0, \psi_s(u) \ge 0, \kappa_s(u,v) \ge 0 \\
\quad \forall \text{ pairs } i \to j: p_s(i,j) \ge 0, p_s(i,i) = 0
\end{array}
\tag{20}
$$

LP (15) can be regarded as a special case of LP (20). When we have no knowledge of the traffic pattern, i.e., the range is $[0, +\infty]$, the LP to compute the oblivious routing, LP (15), can be obtained from LP (20) by removing the constraints, $\forall$ nodes $s, \forall$ nodes $i, j \neq i : \sum_i \{w_s^-(i,j)a_{i,j} - w_s^+(i,j)b_{i,j}\} \ge 0$, and the variables $w_s^+(i,j)$ and $w_s^-(i,j)$ for the range restrictions.

Theorem 1. *The traffic-oblivious energy-aware routing of a multihop wireless network can be computed by a polynomial size Linear Program with $O(n^3 + n^2 m)$ variables and $O(n^3 + n^2 m)$ constraints, where n and m are the numbers of nodes and edges.*

We can prove Theorem 1 when we develop the LP model.

C. A Single Sink Case

The multihop wireless network with a single sink is a special case of communication over multihop wireless networks. An exception is the sink is usually supposed to have infinite energy. A potential application is wireless sensor networks.

With a single sink, the traffic matrix is reduced to a traffic vector, with each entry d_i denoting the amount of traffic originating from i. Routing $\mathbf{f}$ is defined as:

$$
\begin{cases}
\forall \text{ nodes } i \neq T: \sum_{(i,j)\in out(i)} f_i(i,j) = 1 \\
\forall \text{ nodes } i \neq T, \forall k \neq i, T: \\
\quad \sum_{(k,l)\in out(k)} f_i(k,l) - \sum_{(j,k)\in in(k)} f_i(j,k) = 0 \\
\forall i \neq T, \forall \text{ edges } (s,t): f_i(s,t) \ge 0
\end{cases}
\tag{21}
$$

With approximate knowledge of the traffic pattern in the form that d_i is within the range $[a_i, b_i]$, we can compute the oblivious routing of a multihop wireless network with a single sink by a polynomial size LP. It has $O(n^2 + nm)$ variables and $O(n^2 + nm)$ constraints. We give the LP directly:

$$
\begin{array}{l}
\min r \\
\mathbf{f} \text{ is a routing} \\
\forall \text{ nodes } s \neq T: \\
\quad \sum_{u\neq T} \{\pi_s(u)pow(u) + \sum_v \kappa_s(u,v)c(u,v) + \beta\psi_s(u)\} \le r \\
\quad \forall \text{ nodes } i \neq T: \\
\quad\quad p_s(i) + w_s^+(i) - w_s^-(i) \ge \\
\quad\quad \frac{1}{pow(s)}\{ \sum_{t:(s,t)\in E} \{\gamma_{st} f_i(s,t) tx(s,t)\} \\
\quad\quad\quad + \sum_{t:s\in nbr(t)} \{f_i(t,s)r(s)\} \\
\quad\quad\quad + \sum_{t:s\in nbr(t)} \sum_{k:k\in nbr(t,-s)} \{I_{(t,s)}^{(t,k)} \frac{\gamma_{tk} f_i(t,k)}{\gamma_{ts}} h(s)\}\} \\
\quad \forall \text{ edges } (u,v), u \neq T: \\
\quad\quad tx(u,v)\pi_s(u) + \frac{r(v)}{\gamma_{uv}}\pi_s(v) \\
\quad\quad + \sum_{k:k\in nbr(u,-v)} I_{(u,k)}^{(u,v)} \frac{h(k)}{\gamma_{uv}} \pi_s(k) \\
\quad\quad - p_s(u) + p_s(v) + \kappa_s(u,v) + \frac{\psi_s(u)}{c(u,v)} + \frac{\psi_s(v)}{c(v,u)} \ge 0 \\
\quad \sum_{u\neq T} \pi_s(u) > 0 \\
\quad \forall \text{ nodes } i \neq T: \sum_i \{w_s^-(i)a_i - w_s^+(i)b_i\} \ge 0 \\
\quad \forall \text{ nodes } i \neq T: \pi_s(i), p_s(i), w_s^+(i), w_s^-(i) \\
\quad \forall \text{ nodes } u,v: \psi_s(u), \kappa_s(u,v) \ge 0 \\
\quad p_s(T) = 0, \pi_s(T) = 0
\end{array}
\tag{22}
$$

The LP to compute the oblivious routing with no knowledge of traffic pattern can be obtained from LP (22).

D. Interference-free and Lossless

In this section, we give the LP formulations to design traffic-oblivious energy-aware directly when there is no interference and links are lossless.

For the case in which communications may happen between all OD pairs, in LP (23), we directly give the LP model to compute the optimal oblivious ratio for a multihop wireless network, when we know approximate knowledge of the traffic pattern that d_{ij} is within the range of $[a_{ij}, b_{ij}]$. When we have no knowledge of the traffic pattern, i.e., the range is $[0, +\infty]$, the LP to compute the oblivious ratio can be obtained by removing the constraints, $\forall$ nodes $s, \forall$ nodes $i, j \neq i : \sum_i \{w_s^-(i,j)a_{i,j} - w_s^+(i,j)b_{i,j}\} \ge 0$, and the variables $w_s^+(i,j)$ and $w_s^-(i,j)$ for the range restrictions.

$$
\begin{array}{l}
\min r \\
\mathbf{f} \text{ is a routing} \\
\forall \text{ nodes } s: \\
\quad \sum_u \pi_s(u) pow(u) \leq r \\
\quad \forall \text{ nodes } i, j \neq i: \\
\quad\quad p_s(i,j) + w_s^+(i,j) - w_s^-(i,j) \geq \\
\quad\quad\quad \frac{1}{pow(s)}\{ \sum_{t:(s,t)\in E} \{f_{ij}(s,t) tx(s,t)\} \\
\quad\quad\quad\quad + \sum_{t:s\in nbr(t)} \{f_{ij}(t,s) r(s)\} \\
\quad\quad\quad\quad + \sum_{t:s\in nbr(t)} \sum_{u:u\in nbr(t,-s)} \{I_{(t,s)}^{(t,u)} f_{ij}(t,u) h(s)\}\} \\
\quad \forall \text{ nodes } i, \forall \text{ edges } (u,v): \\
\quad\quad tx(u,v)\pi_s(u) + r(v)\pi_s(v) \\
\quad\quad + \sum_{k:k\in nbr(u,-v)} \{I_{(u,k)}^{(u,v)} h(k) \pi_s(k)\} \\
\quad\quad - p_s(u,i) + p_s(v,i) \geq 0 \\
\quad \sum_u \pi_s(u) > 0 \\
\quad \forall \text{ nodes } i, j \neq i: \sum_i \{w_s^-(i,j) a_{ij} - w_s^+(i,j) b_{ij}\} \geq 0 \\
\quad \forall \text{ nodes } u: \pi_s(u) \geq 0 \\
\quad \forall \text{ nodes } i, j \neq i: p_s(i,j), w_s^+(i,j), w_s^-(i,j) \geq 0 \\
\quad \forall \text{ nodes } i: p_s(i,i) = 0
\end{array}
\tag{23}
$$

For a single sink case, when we have approximate knowledge of the traffic pattern in the form that the traffic demand d_i is within the range $[a_i, b_i]$, we can compute the optimal oblivious ratio of a multihop wireless network with a single sink by a polynomial size LP. It has $O(n^2 + nm)$ variables and $O(n^2 + nm)$ constraints. The LP follows:

$$
\begin{array}{l}
\min r \\
\mathbf{f} \text{ is a routing} \\
\forall \text{ nodes } s \neq T: \\
\quad \sum_{u \neq T} \pi_s(u) pow(u) \leq r \\
\quad \forall \text{ nodes } i \neq T: \\
\quad\quad p_s(i) + w_s^+(i) - w_s^-(i) \geq \\
\quad\quad\quad \frac{1}{pow(s)}\{ \sum_{t:(s,t)\in E} \{f_i(s,t) tx(s,t)\} \\
\quad\quad\quad\quad + \sum_{t:s\in nbr(t)} \{f_i(t,s) r(s)\} \\
\quad\quad\quad\quad + \sum_{t:s\in nbr(t)} \sum_{k:k\in nbr(t,-s)} \{I_{(t,s)}^{(t,k)} f_i(t,k) h(s)\}\} \\
\quad \forall \text{ edges } (u,v), u \neq T: \\
\quad\quad tx(u,v)\pi_s(u) + r(v)\pi_s(v) \\
\quad\quad + \sum_{k:k\in nbr(u,-v)} I_{(u,k)}^{(u,v)} h(k)\pi_s(k) - p_s(u) + p_s(v) \geq 0 \\
\quad \sum_{u \neq T} \pi_s(u) > 0 \\
\quad \forall \text{ nodes } i \neq T: \sum_i \{w_s^-(i) a_i - w_s^+(i) b_i\} \geq 0 \\
\quad \forall \text{ nodes } i \neq T: \pi_s(i), p_s(i), w_s^+(i), w_s^-(i) \geq 0 \\
\quad p_s(T) = 0, \pi_s(T) = 0
\end{array}
\tag{24}
$$

E. Generalization

Energy Consumption Model. The energy consumption model $\mathbf{energy}_s$ (5) is general enough to take into account several issues in radio transmission. By properly defining the indicator function, we can handle the case in which a node can vary its transmission range with arbitrary precision, at several discrete levels, or with a fixed transmission range. Note a node may transmit on different links with different power; but the power on a link is constant.

For example, assume a disk model for radio transmission, i.e., the maximum transmission range is the same in different directions. Also assume omni-directional transmission. When a node can vary its transmission range with arbitrary precision, the indicator function is defined as,

$$
I_{(t,s)}^{(t,k)} = \begin{cases} 1 & \text{if } dist(t,k) \geq dist(t,s); \\ 0 & \text{otherwise.} \end{cases}
$$

When there are n_t transmission ranges for a wireless node t, $r_1, r_2, ..., r_{n_t}$, with $r_1 < r_2 < ... < r_{n_t}$, we need to replace $dist(t,k)$ with r_i, where $r_i \geq dist(t,k)$, and if $i \neq 1$, $r_{i-1} < dist(t,k)$. That is, we replace $dist(t,k)$ with the smallest transmission range which is $\geq dist(t,k)$. We have,

$$
I_{(t,s)}^{(t,k)} = \begin{cases} 1 & \text{if } r_i \geq dist(t,s); \\ 0 & \text{otherwise.} \end{cases}
$$

In the case where the transmission range for node t is fixed, denoted as $TxR(t)$, we can obtain the proper indicator function by replacing r_i with $TxR(t)$.

As well, we can handle the radio irregularity problem studied recently, e.g. in [27], that a radio has different maximum transmission ranges in different directions. This affects the neighboring relationship. The energy model can be used for the wireless communication using either omni-directional antenna or smart antenna. For smart antenna with directional communication, the model for transmission $tx(s,t)$ and reception $r(s)$ need to include a component to account for the energy consumption for managing the antenna.

Multi-channel and multi-radio. In a wireless network with multi-channel and/or multi-radio, there will be multiple edges between a pair of nodes in a graph representation. The LP models still work on this multigraph. The channels operated by a radio usually interfere with each other. But there is no interference among channels operated by multiple radios orthogonal with each other. The work to handle interference in Kodialam and Nandagopal [14] and Jain et al. [12] are applicable here. Interference issues will be further discussed in Section III-D. The LP models is thus extensible to a multi-input multi-output (MIMO) system.

F. Implementation Issues

For a stationary network, our tools only need to collect the topology and initial energy level once. It is possible to construct the graph of the network with good links, using the techniques in Woo et al. [27] to estimate link quality. The criteria for the goodness of link quality is that its average quality is good and relatively stable. After that, we take a centralized way to compute the optimal oblivious routing. We need a round of message exchanges to implement the routing. Once the routing is implemented, it does not need to collect global network information any more. With only two rounds of message exchanges, our approach has a low message complexity. Once the routing is implemented, it is fully distributed. In contrast, the distributed algorithms in [8], [13], [25], [24] and the hierarchical algorithm in [16] need to collect network information such as the remaining energy level from time to time.

The routing computed by our LP model can be implemented in an opportunistic manner, i.e., each node transmits data packets opportunistically to its neighbors according to the fraction specified by the routing. Such an implementation has the potential to combat the fluctuating channel condition in practice. This is achieved by monitoring the outgoing links and choosing the one with good quality at the time of transmission. Recently there are experimental results on link quality estimation, e.g. Woo et al. [27]. We can exploit their techniques to estimate the variation of link quality caused by temporary link failures and interference. The estimate of link quality and the routing fraction determine which link to transmit a packet. This is amiable to a distributed implementation, in which each node only needs to monitor the quality of the neighboring links. Once the fraction of traffic load on each link is satisfied, the energy efficiency is accomplished. In this way, our "single fixed" routing makes "rerouting" transparently. The randomization of the routing could help alleviate the impact of channel quality fluctuation.

In an energy-constrained multihop wireless network, when one or several nodes have used up energy, they are disconnected from the network. The network may still be working for a while. Reoptimizition of the routing may be needed. A similar problem, how to optimize the "oblivious restoration" when one or several nodes fail in the scenario of the Internet, is studied in [3]. We may use similar techniques to obtain an optimal oblivious restoration. However, collecting remaining energy capacities consumes energy. Thus, further investigation is needed to justify the benefit of routing reoptimization. A simple approach is to bypass the failed node(s) by assigning additional fraction of flows on the upstream nodes whose flow passes the failed node. The assignment of the fraction on an upstream node is determined by the fraction of the flow passing the node, in an attempt to balance the load. This simple approach of shifting flow away the failed node is amiable to a distributed implementation.

V. Performance Study

We study the performance of the LP models for multihop wireless networks where energy is a constraint and non-renewable. We use random topologies. We put nodes on a $k \times k$ grid, each cell of which represents a $10m \times 10m$ area. In each cell of the grid, we put a node at a random position. The initial energy level of each node is set randomly, uniformly within $[20J, 30J]$ (note the oblivious ratio is invariant with the scaling of the initial energy level). For brevity, we use a disk model for radio transmission. That is, suppose the maximum transmission range of node u is R_{max}, there is an edge (u, v) if $R_{max} \geq dist(u, v)$, where $dist(u, v)$ denotes the distance between u and v. In the simulations, every node has the same maximum transmission range of 15m. Loss ratio of each edge is uniformly set within $[0\%, 50\%]$. We set $\beta = \frac{2}{3}$ for schedulability constraint (6). We use CPLEX [1] to solve the LP programs.

We use the energy model in [11], i.e., we set $tx(u, v) = E_{elec} + \epsilon_{amp} \times dist^2(u, v)$ and $r(u) = E_{elec}$, where E_{elec} represents the energy consumption for running the transmitter or the receiver circuitry, ϵ_{amp} represents the energy consumption for running the transmitter amplifier to achieve an acceptable signal-noise ratio. We set $h(u) = r(u)$, i.e., we assume that the overhearing consumes the same amount of energy per unit of message as the reception. As in [11], we set $E_{elec} = 50nJ/bit$ and $\epsilon_{amp} = 100pJ/bit/m^2$.

A. *Interference-limited, Lossy Links*

We study topologies with 25 nodes. We conduct experiments of 8 runs with different seeds. We use LP (15) to compute the oblivious ratios. The min and max of the oblivious ratios of the studied networks are shown in the last column in Table I under the error margin ∞ (which means we have no knowledge of the traffic pattern, as will be clear later). These results are encouraging, since they are achieved without any knowledge of the traffic pattern and without ongoing network information collection; while only an oracle can achieve a ratio of 1.0.

It is expected that with some knowledge of traffic demands, we can achieve lower oblivious ratios. In the following we study the performance of LP (20) if we know the degree of accuracy of the traffic estimation, for a topology, a traffic matrix $\mathbf{tm}$ and an "error margin" $\varepsilon > 1$. We will study the oblivious ratio of a network, given the knowledge of traffic demand in the form of $d_{ij}/\varepsilon \leq d_{ij} \leq \varepsilon d_{ij}$. First, we need to decide the base traffic matrix, i.e., the d_{ij}'s.

We may have some rough estimation of the traffic pattern in a multihop wireless network. We use four traffic models to determine the base traffic matrix $\mathbf{tm}$: Gravity, Bimodal, Random and Uniform, to attempt to capture some broad classes of traffic patterns in multihop wireless networks. They are denoted as G, B, R and U respectively in the tables. In the Gravity model, the amount of traffic of the OD pair d_{ij} is proportional to $pow(i) \times pow(j)$, the product of the initial energy capacities of nodes i and j. In the Bimodal, a small portion of pairs have a large amount of traffic, while a large number of pairs have small amount of traffic. In our study, 20% pairs have traffic demands determined by $N(10.0, 1.0)$, while 80% pairs determined by $N(1.0, 0.1)$. Random model is self-explanatory. In our study, we use a uniform distribution on the range $[1, 100]$. In a Uniform model, all the OD pairs have the same amount of traffic. The Gravity and the Bimodal traffic models are inspired by the study on the Internet traffic estimation in [28] and [7] respectively, which may reflect the technical expectation to and the social phenomenon of a network (the Internet). In a wireless network, we may imagine that a node with high energy capacity may tend to transmit more data. It is possible that, in some applications, some “hotspot” area may have much more information to transmit.

With rough knowledge of the traffic pattern, the oblivious ratios can be much lower than that without any knowledge of traffic. The min and max of the oblivious ratios of the studied networks with approximate knowledge of the traffic pattern are shown in Table I under the error margin $1.5, 2.0$ and 3.0. These are computed by LP (20). With error margin $\varepsilon = 1.5$, we can achieve a fixed routing that is at most $76.53\% - 84.24\%$ (the max value) worse than the oracle; while the ratio can be as low as 1.3652 (the min value). There is a clear trend that when we have more accurate knowledge of the traffic pattern, i.e. when $\varepsilon > 1$ gets smaller, the oblivious ratio is lower.

TM		1.5	2.0	3.0	∞
U	min	1.4250	1.6260	1.7734	
	max	1.7852	1.9657	2.1674	
G	min	1.4265	1.6144	1.7719	2.6742
	max	1.7797	1.9692	2.1729	(min)
B	min	1.3652	1.5301	1.6766	
	max	1.7653	1.9589	2.1521	3.1648
R	min	1.4634	1.6832	1.8934	(max)
	max	1.8424	2.0746	2.2910	

TABLE I

MIN AND MAX OBLIVIOUS RATIOS OVER 8 RUNS: ALL PAIR CASE

We also conduct experiments for multihop wireless networks with a single sink for topologies of 81 nodes. The sink is in the center cell. We conduct experiments of 8 runs with different seeds and report the min and max of the oblivious ratios. In the Gravity model, the amount of traffic originating from node i, d_i, is proportional to $pow(i)$, the initial energy level of node i. In the Bimodal, a small portion of nodes have a large amount of traffic, while a large number of nodes have small amount of traffic. In our study, 80% nodes have traffic demands determined by a normal distribution $N(1.0, 0.1)$; while traffic demands of 20% nodes are determined by $N(10.0, 1.0)$. For Random model, we use a uniform distribution on the range $[1, 100]$. In a Uniform model, all the nodes have the same amount of traffic. We use LP (22) and its derivation for knowing no knowledge of traffic pattern to compute the oblivious ratios. Experimental results in Table II show that we can achieve a performance close to that an oracle can achieve. With fairly approximate knowledge of the traffic pattern, e.g. with error margin $\varepsilon = 1.5$, the oblivious ratios are fairly low, between 1.1831 and 1.6096.

TM		1.5	2.0	3.0	∞
U	min	1.1831	1.3320	1.6252	
	max	1.5835	1.6356	1.9240	
G	min	1.1838	1.3330	1.6279	2.4117
	max	1.5848	1.6382	1.9204	(min)
B	min	1.2378	1.4380	1.6249	
	max	1.5506	1.7279	2.0580	2.7418
R	min	1.2684	1.3895	1.5625	(max)
	max	1.6096	1.6688	1.9251	

TABLE II

MIN AND MAX OBLIVIOUS RATIOS OVER 8 RUNS: A SINGLE SINK

N	R_{max}	TM	1.5	2.0	3.0	∞
49	15m	U	1.2264	1.3892	1.5808	1.8239
		G	1.2256	1.3879	1.5810	
		B	1.2612	1.4430	1.5831	
		R	1.2177	1.3773	1.5815	
	20m	U	1.2852	1.4884	1.7138	1.9651
		G	1.2846	1.4875	1.7163	
		B	1.3018	1.5169	1.6943	
		R	1.2954	1.4955	1.6772	
81	15m	U	1.1441	1.2725	1.5154	1.9964
		G	1.1439	1.2727	1.5169	
		B	1.1406	1.2824	1.4966	
		R	1.1377	1.2681	1.5208	
	20m	U	1.1605	1.3086	1.5650	2.0242
		G	1.1600	1.3080	1.5663	
		B	1.1883	1.3493	1.5819	
		R	1.1576	1.3037	1.5544	
100	15m	U	1.0673	1.1442	1.3221	1.9065
		G	1.0669	1.1429	1.3195	
		B	1.0887	1.1851	1.3901	
		R	1.0556	1.1273	1.3037	
	20m	U	1.0920	1.1834	1.3761	1.9752
		G	1.0918	1.1825	1.3743	
		B	1.1219	1.2360	1.4676	
		R	1.0995	1.1923	1.3872	
121	15m	U	1.0604	1.1268	1.3012	1.9071
		G	1.0609	1.1268	1.3007	
		B	1.0780	1.1529	1.3373	
		R	1.0573	1.1305	1.3166	
	20m	U	1.0883	1.1886	1.4129	2.0751
		G	1.0875	1.1874	1.4113	
		B	1.0784	1.2016	1.4803	
		R	1.0960	1.2007	1.4263	

TABLE III

OBLIVIOUS RATIOS: SINGLE SINK IN THE CENTER

B. Interference-free, Lossless Links

A Single Sink Case

We first study a single sink case. We conduct experiments on networks of sizes 25, 36, 49, 81, 100 and 121. We choose the node either in the center or corner cell as the sink.

Tables III shows the oblivious ratios and the results for the sink in the center with the error margin ε of 1.5, 2.0 and 3.0, for the four base traffic models respectively. For each network size N, each maximum transmission range R_{max}, the oblivious ratios for the four base traffic models are on the same topology. We can see that LP (22) can achieve fairly low oblivious ratio with large error margins. Note that, with 50% error in traffic estimation, the performance is close to the optimal (the oblivious ratio is close to 1.0). To save space, we do not present results for networks of sizes 25 and 36. They have similarly low oblivious ratios.

When the sink is in the corner, the oblivious ratio can be much lower. We conduct experiments with 9 seeds for the random number generator, which may change the locations of the nodes (thus the graph), the initial energy level and the base traffic matrix (for Bimodal and Random model). In Table IV, we show the min and max of the oblivious ratios over 9 seeds for Uniform model for the case the sink is in the corner for

N	R_{max}		1.5	2.0	3.0	∞
49	15m	min	1.000+	1.000+	1.000+	1.000+
		max	1.2329	1.3946	1.6091	1.9340
	20m	min	1.0100	1.0203	1.0438	1.1800
		max	1.3771	1.5880	1.7750	1.9767
81	15m	min	1.000+	1.000+	1.000+	1.0353
		max	1.0945	1.2125	1.4442	1.9652
	20m	min	1.0044	1.0090	1.0224	1.1872
		max	1.1706	1.3402	1.6354	2.0770

TABLE IV

MIN AND MAX OBLIVIOUS RATIOS OVER 9 RUNS: A SINGLE SINK IN THE CORNER (UNIFORM BASE TM)

N	R_{max}	TM	1.5	2.0	3.0	∞
49	75m	G	1.2985	1.4891	1.7232	2.1356
		R	1.3110	1.5294	1.7328	
	100m	G	1.3128	1.5465	1.8378	2.2395
		R	1.3405	1.5877	1.8332	
81	75m	G	1.1102	1.2111	1.4423	2.1934
		R	1.0987	1.1957	1.4251	
	100m	G	1.1580	1.3206	1.6335	2.2678
		R	1.1615	1.3331	1.6350	
100	75m	G	1.0419	1.0886	1.1973	1.9786
		R	1.0427	1.0840	1.2036	
	100m	G	1.0720	1.1539	1.3308	2.1054
		R	1.0659	1.1404	1.3253	
121	75m	G	1.0372	1.0713	1.1648	1.9499
		R	1.0317	1.0605	1.1899	
	100m	G	1.0764	1.1545	1.3463	2.3008
		R	1.0572	1.1310	1.3324	

TABLE V

OBLIVIOUS RATIOS: A SINGLE SINK IN THE CENTER, TRANSMISSION DOMINATES ENERGY CONSUMPTION

49 nodes and 81 nodes. The results of 1.000+ represent those slightly greater than 1.0.

The energy consumption for reception and overhearing may be insignificant in some cases such as long-range transmission. We attempt to study how our LP models perform under such circumstances. We still use a $k \times k$ grid. However, each cell of the grid represents a $50m \times 50m$ area. we study two maximum transmission ranges, 75m and 100m. Recall we set $tx(u,v) = E_{elec} + \epsilon_{amp} \times dist^2(u,v)$ and $r(u) = h(u) = E_{elec}$. Thus the distance plays an important role in energy consumption. It seems that our LP models perform similarly over the four base traffic models. In this set of experiments, we use the Gravity model and Random model to determine the base traffic matrix when we have approximate knowledge of the traffic pattern. Experimental results in Table V shows that when the energy consumption for reception and overhearing is less significant, our LP models can achieve low oblivious ratios, especially when we have some weak knowledge of the traffic pattern. We achieve low oblivious ratios when the sink is in the corner.

We also conduct experiments using the energy model in [16], where $tx(u,v) = 0.0001 \times dist^3(u,v)$. Since the reception and overhearing are not considered in [16], we set $h(u) = r(u) = 0$. We obtain similarly low oblivious ratios.

All Pair Case

Next we study the all pair case. We study topologies of sizes 25 and 36. The oblivious ratios of the studied networks are shown in the last column in Table VI (denoted by the error margin ∞). These results are encouraging, since they are achieved without any knowledge of the traffic pattern and without the ongoing network information collection.

Similarly to Section V-A, we use four traffic models to determine the base traffic matrix $\mathbf{tm}$, when we have approximate knowledge of the traffic pattern. In the Gravity model, the amount of traffic of the OD pair d_{ij} is proportional to $pow(i) \times pow(j)$, the product of the energy capacities of nodes i and j. In the Bimodal, 20% pairs have traffic demands determined by $N(10.0, 1.0)$, while 80% pairs determined by $N(1.0, 0.1)$. We use a uniform distribution on $[1, 100]$ for the Random model. In a Uniform model, all the OD pairs have the same amount of traffic.

With rough knowledge of the traffic pattern, the competitive ratios can be much lower than that without any knowledge of traffic. With error margin $\varepsilon = 1.5$, we can achieve a fixed routing that is at most $33.5\% - 46.5\%$ worse than the oracle optimal routing. We do not intend to claim that for all the topologies we can achieve a competitive ratio within this range. It may be lower or higher. The competitive ratio depends on the topology and the relative energy capacity levels. If the oblivious ratio is acceptably low, the fixed routing is a competitive option for optimizing energy efficiency.

N	R_{max}	TM	1.5	2.0	3.0	∞
25	15m	U	1.3351	1.4928	1.6532	2.1671
		G	1.3346	1.4924	1.6532	
		B	1.3357	1.4925	1.6516	
		R	1.3318	1.4882	1.6448	
	20m	U	1.3732	1.5451	1.7113	2.2237
		G	1.3730	1.5449	1.7110	
		B	1.3575	1.5306	1.7030	
		R	1.3713	1.5418	1.7086	
36	15m	U	1.4287	1.6151	1.8094	2.4054
		G	1.4288	1.6151	1.8097	
		B	1.4277	1.6143	1.8019	
		R	1.4237	1.6134	1.8085	
	20m	U	1.4642	1.6826	1.8866	2.4397
		G	1.4646	1.6830	1.8870	
		B	1.4575	1.6819	1.8827	
		R	1.4648	1.6831	1.8866	

TABLE VI

OBLIVIOUS RATIOS: ALL PAIR CASE

We also conduct experiments in the case that each cell of the grid represents a $50m \times 50m$ area to attempt to study how the LP models perform in multihop wireless networks when the energy consumption for reception and overhearing is less significant. we use two maximum transmission ranges, 75m and 100m. We use the Gravity model and Random model when we know the range restriction on the base traffic matrix. Table VII shows that our LP models can achieve low oblivious ratios (close to the optimal performance).

N	R_{max}	TM	1.5	2.0	3.0	∞
25	75m	G	1.4048	1.6377	1.8718	2.4018
		R	1.4054	1.6297	1.8647	
	100m	G	1.4868	1.7438	1.9655	2.4098
		R	1.4813	1.7342	1.9547	
36	75m	G	1.4253	1.6596	1.9346	2.6166
		R	1.4309	1.6652	1.9386	
	100m	G	1.5215	1.8107	2.1031	2.6479
		R	1.5230	1.8113	2.1039	

TABLE VII

OBLIVIOUS RATIOS: ALL PAIR CASE, TRANSMISSION DOMINATES ENERGY CONSUMPTION

VI. CONCLUSIONS

Energy efficiency is an important issue in multihop wireless networks with energy concerns. We investigate the problem of designing traffic-oblivious energy-aware routing to minimax the energy utilization in multihop wireless networks in scenarios where 1) there is no interference and links are lossless, and 2) interference is present and links are lossy. We design LP models of polynomial sizes in both the number of variables and the number of constraints with a fairly weak assumption of the traffic pattern. With no or approximate knowledge of the traffic pattern, our LP models can achieve the performance close to that an oracle can achieve (with oblivious ratios close to 1). The performance is particularly good in the case of multihop wireless networks with a single sink.

Our LP model is general enough to model various wireless systems, such as MIMO. The routing can work well in an interference-free wireless network. In an interference-limited scenario, we can guarantee schedulability of the oblivious routing. In a lossy environment, we study energy efficiency under a reliable routing scheme. We discuss considerations in implementation. With several issues to further study and implementation details to fulfill, we make a first stride in designing a traffic-oblivious energy-aware routing framework in multihop wireless networks.

It is interesting to compare our work with an adaptive approach that uses energy efficiently for information collection, e.g. [13]. We also plan to investigate applicability of the clustering technique to our routing scheme and more QoS concerns such as end-to-end delay constraints.

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