On the Interdependence of Distributed Topology Control and Geographical Routing in Ad Hoc and Sensor Networks

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***Abstract*—Since ad hoc and sensor networks can be composed of a very large number of devices, the *scalability* of network protocols is a major design concern. Furthermore, network protocols must be designed to prolong the battery lifetime of the devices. However, most existing routing techniques for ad hoc networks are known not to scale well. On the other hand, the so-called *geographical routing algorithms* are known to be scalable but their energy efficiency has never been extensively and comparatively studied. In a geographical routing algorithm, data packets are forwarded by a node to its neighbor based on their respective positions. The neighborhood of each node is constituted by the nodes that lie within a certain radio range. Thus, from the perspective of a node forwarding a packet, the next hop depends on the width of the neighborhood it perceives. The analytical framework proposed in this paper allows to analyze the relationship between the energy efficiency of the routing tasks and the extension of the range of the topology knowledge for each node. A wider topology knowledge may improve the energy efficiency of the routing tasks but increases the cost of topology information due to signaling packets needed to acquire this information. The problem of determining the *optimal topology knowledge range* for each node to make energy efficient geographical routing decisions is tackled by integer linear programming. It is shown that the problem is intrinsically localized, i.e., a limited topology knowledge is sufficient to make energy efficient forwarding decisions. The leading forwarding rules for geographical routing are compared in this framework, and the energy efficiency of each of them is studied. Moreover, a new forwarding scheme, *partial topology knowledge forwarding* (PTKF), is introduced, and shown to outperform other existing schemes in typical application scenarios. A *probe-based distributed protocol for knowledge range adjustment* (PRADA) is finally introduced that allows each node to efficiently select online its topology knowledge range. PRADA is shown to rapidly converge to a near-optimal solution.**

***Index Terms*—Geographical routing, mathematical programming/optimization, topology control, wireless ad hoc and sensor networks.**

I. Introduction

RECENT ADVANCES in wireless communications and electronics are paving the way for the deployment of low-cost, low-power, large scale ad hoc networks such as untethered and unattended networks of sensors and actuators. Sensor networks [1] differ from "traditional" ad hoc networks in many aspects. The number of nodes in a sensor network can be several orders of magnitude higher than in ad hoc networks, and the deployment of nodes is usually denser. Moreover, sensor nodes are limited in power, computational capacities and memory, and they may not have *global identification* (ID) because of the very large number of nodes and the related overhead.

Due to the above constraints, sensor network protocols and algorithms must be endowed with self-organizing capabilities, i.e., sensors must be able to cooperate in order to efficiently perform networking tasks. The primary design constraints of these algorithms are *energy efficiency, scalability* and *localization*.

It has been recently pointed out [2] that energy efficiency in mobile systems can be improved by designing protocols and algorithms with a *cross-layer approach*, i.e., by taking into account interactions among different layers of the communication process so that the overall energy consumption can be minimized. Hence, in this paper, we consider interdependencies between physical and network layer functionalities to improve the energy efficiency of the routing tasks.

A primary requirement of configuration algorithms for large scale ad hoc networks, such as routing algorithms, is *scalability*, i.e., these algorithms should perform well for wireless networks with an arbitrary number of nodes. The notion of scalability is tightly related to that of *localization*: in a scalable algorithm each node exchanges information only with its neighbors (*localized* information exchange) [3]. In a *localized routing algorithm*, each node selects the next hop based only on the position of itself, of its neighbors, and of the destination node. As a result, the local routing decision of each node strives to achieve a global network objective such as minimum latency or minimum energy consumption. Conversely, in a nonlocalized routing algorithm a node maintains an accurate description of the overall network topology to select the next hop. This way, the routing problem is equal to the shortest path problem if the *hop count* is used as the global performance metric, or the shortest weighted path if *power* [4] or *cost* [5], [6] link metrics are used.

It has been shown [7], [8] that routing protocols that do not use geographical location information are not scalable, e.g., ad hoc on-demand distance vector (AODV), destination sequenced distance vector (DSDV), or dynamic source routing (DSR). On the other hand, the recent availability of small, inexpensive and low-power Global Positioning System (GPS) receivers, together with techniques to deduce relative sensor coordinates from signal strengths [9] encourage researchers to develop

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geographical routing [10] (also, *position-based routing*) algorithms, which are deemed to be the most promising solutions for critically power-constrained ad hoc networks.

For these reasons, this paper deals with the interdependencies between topology control [11] and energy efficient geographical routing. The question we try to answer is "*How extensive should be the local knowledge of the global topology in each node, so that energy efficient geographical routing decisions can be taken?*" The answer to the question is clearly related to the "degree" of localization of the routing scheme. If each node could hold a complete vision (knowledge) of the network topology, it could then compute the "globally" optimal next hop, i.e., the neighboring node on the minimum energy path. However, acquiring increasingly accurate topology information has an increasing cost, i.e., the energy required to exchange the signaling traffic that conveys this information.

Hence, we develop an analytical framework to capture the tradeoff between what we refer to as the *topology information cost*, which increases with increasing range of knowledge of each node, and the *communication cost*, which may decrease when the knowledge becomes more complete. We apply this analytical framework to different position-based forwarding schemes [12]–[16] and show by Monte Carlo simulations that a limited knowledge is sufficient to make energy efficient routing decisions. With respect to the existing literature on geographical routing, we try to better define the terms "localized" and "neighbor." A "neighbor" for a certain node is another node which falls into its *topology knowledge range*, denoted as KR in the following.

The main contributions of this paper are the following.

- We introduce an *analytical framework* to evaluate the energy consumption of geographical routing algorithms for power-constrained large scale ad hoc networks.
- We provide an integer linear programming (ILP) formulation of the *topology knowledge range* optimization problem.
- We conduct a detailed comparison of the leading existing forwarding schemes and introduce a new scheme called partial topology knowledge forwarding (PTKF).
- We introduce a probe-based distributed protocol for knowledge range adjustment (PRADA), that allows each node to efficiently select online its topology knowledge range, and show that PRADA leads to near-optimal energy consumption.

The remainder of this paper is organized as follows. In Section II, we review existing forwarding schemes for geographical routing and other related work. In Section III, we state the problem and in Section IV, we formulate it as an optimization problem. In Section V, we introduce PRADA, a distributed protocol for online knowledge range adjustment. In Section VI, we show numerical performance results, while in Section VII, we conclude the paper and draw the main conclusions.

II. Related Work

In this section, we describe the existing position-based forwarding rules that will be compared in the following of the paper, and review other existing work on the topic which constitutes the background of our work.

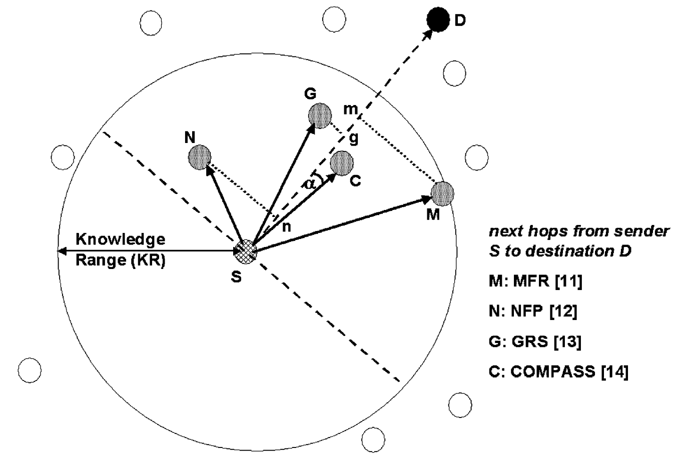


Fig. 1. Different forwarding schemes.

A. Forwarding Rules

In a localized geographical routing scheme, node S (Fig. 1) which currently holds the message, only knows the position of its neighbors, i.e., the nodes within its knowledge range, and of the destination node D. For the convenience of the reader, let us introduce the following definitions.

Definition 1: Given a sender node S and a destination node D, the *progress* of a generic node X is the orthogonal projection of the line connecting S and X onto the line connecting S and D.

Definition 2: Given a sender node S and a destination node D, the *advance* of a generic node X is the distance between S and D minus the distance between X and D.

Takagi and Kleinrock proposed the first geographical routing scheme, based on the notion of progress. In their most forward within radius (MFR) scheme [12], the message is forwarded to the maximum progress neighbor, e.g., node M in Fig. 1, whose progress is $\overline{Sm}$. Note that although node G is closer to the destination, its progress $\overline{Sg}$ is smaller than $\overline{Sm}$. Hou and Li [13] discuss the nearest forward progress (NFP) method which selects the minimum progress neighbor within the topology knowledge range of S, e.g., node N in Fig. 1, whose progress is $\overline{Sn}$. Finn [14] proposes the greedy routing scheme (GRS), which is based on geographical distance: node S selects among its neighbors the closest to the destination, i.e., the node with maximum advance, e.g., G in Fig. 1. In the so-called *compass routing* method [15], the message is forwarded to a neighbor, e.g., C in Fig. 1, such that the angle $\angle$CSD is minimum, i.e., the direction SC is the closest to the direction SD. The random progress forwarding (RPF) method [16] selects a random next hop among the nodes within the knowledge range.

A sufficient condition for a geographical routing scheme to be loop free is that only next-hop nodes with positive *advance* can be selected. According to Definition 2, a generic node has a positive advance with respect to a sender node if it is closer than the sender to the destination. When a routing scheme is constrained to select a node as next hop only if it has positive advance, then

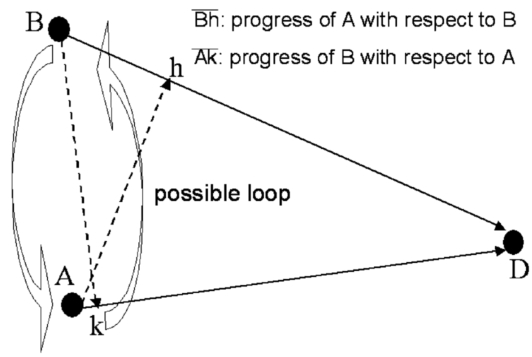


Fig. 2. Counterexample on the notion of progress.

the overall path is guaranteed to be loop free. Conversely, a positive progress for each next hop is not a sufficient condition for a routing scheme to be loop free, as can be inferred from the counterexample in Fig. 2, where three nodes, A, B, and a destination node D are shown. A is a possible next hop for B and *vice versa*, since both nodes A and B have positive progress with respect to each other $(\overline{Ak} > 0, \overline{Bh} > 0)$. However, this does not avoid loops as both nodes could choose the other as next hop, although as shown in [17] the two nodes can recognize the loop and stop it. Referring again to the example in Fig. 2, when a positive advance is a necessary condition for a node to be next hop, A is a feasible next hop for B, but not *vice versa*, since A is closer than B to the destination $(\overline{AD} < \overline{BD})$. Since positive advance is a stronger condition, and guarantees loop free paths, we take positive advance as a necessary condition for a node to be the next hop. In other words, a node must choose the next hop among the nodes within its knowledge range *and* with positive advance with respect to the destination node, for all the considered forwarding schemes.

B. Other Related Work

An excellent survey on position-based routing techniques for ad hoc networks is given in [10] and [18]. Location update techniques, i.e., methods to determine absolute and relative coordinates for network nodes, are reviewed in [19].

Most of the prior research assumes that nodes can either work in a *greedy mode* or in a *recovery mode*. When in greedy mode, the node that currently holds the message tries to forward it toward the destination. The recovery mode is entered when a node fails to forward a message in the greedy mode, since none of its neighbors is a feasible next hop. Usually, this occurs because the node observes a void region between itself and the destination. Such a node is referred to as *concave* node. For example, the GFG algorithm [20] makes *greedy* forwarding decisions (as GRS in Section II-A). When a packet reaches a concave node, GFG tries to recover by routing around the perimeter of the void region. Recovery mechanisms, which allow a packet to be forwarded to the destination when a concave node is reached, are out of the scope of this paper. Here, we assume that the packet is directly forwarded to the destination whenever such a node is reached.

The trajectory-based forwarding (TBF) algorithm is proposed in [21], where the packet is forwarded along a predefined parametric curve encoded in the packet at the source. Several localized algorithms for power, cost and power-cost efficient routing are proposed, and their efficiency is analyzed in [22]. Scalability properties of different ad hoc routing techniques such as flat, hierarchical, and geographical routing are discussed in [23]. The GAF topology control algorithm [24] identifies nodes that are equivalent from a routing perspective based on position information, and adaptively turns unnecessary nodes off in order to maintain a constant level of performance.

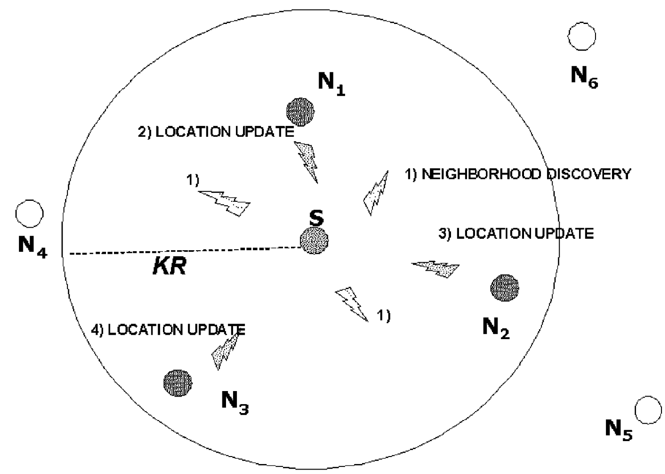


Fig. 3. Neighborhood discovery protocol.

A taxonomy of location systems is given in [9] for ubiquitous computing applications, including location sensing techniques and properties, as well as a survey of commercially available location systems. In [25], it is shown how to derive position information for all nodes using angle-of-arrival (AOA) capabilities, when only a fraction of the nodes have positioning capabilities. Finally, a distributed location service (GLS) is described in [7], where a node sends its position updates to its location servers without knowing their actual identities. This information is then used by the other nodes in the network to perform geographical routing operations.

III. Problem Setup

In this section, we introduce the *topology knowledge range* problem, which is then formulated as an ILP in Section IV. First, we describe a neighborhood discovery protocol which allows each node to gather information about its neighborhood. Then, we introduce the network and energy models and define some useful notions. Finally, we present a new localized forwarding scheme called PTKF.

Let us consider the following neighborhood discovery protocol. With reference to Fig. 3, node S periodically sends a neighborhood discovery packet (ND-packet) to gather localization information about its neighbor nodes, at a power level that allows the packet to be received by all nodes within its chosen knowledge range (KR in Fig. 3).

As a result, nodes N_1, N_2, and N_3 receive the ND-packet, while farther nodes do not. All nodes that receive the ND-packet reply with a location update packet (LU-packet), that contains the geographical position of the node. It is intuitive that increasing the KR may result in more efficient routing decisions. However, this comes at the expense of a higher energy consumption needed to exchange signaling traffic. Hence, we are trying to determine the KR for each node so that the energy required by the network to perform the routing tasks is minimized.

A. Network Model

The network is represented as $(\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$ is a finite set of nodes in a finite-dimension terrain, with $N = |\mathcal{V}|$, and where $\mathcal{E}$ is the matrix whose element (i, j) contains the value of the distance between nodes v_i and v_j. We associate to each node v_k its knowledge range, r_k, based on the neighborhood discovery protocol as explained above. Thus, the array $\underline{\mathbf{R}} = [r_1, r_2, \ldots, r_N]$ describes the KRs of all nodes in the network. Let $\mathcal{S}$ be the set of traffic sources and $\mathcal{D}$ the set of destination nodes. We define $\mathcal{P} = \{(s, d) : s \in \mathcal{S}, d \in \mathcal{D}\}$ as the set of source-destination connections. The information rate of each connection is described by the traffic matrix $P = [p_{ij}]$, where p_{ij} represents the average information rate (bit/s) between a source node $i \in \mathcal{S}$ and a destination node $j \in \mathcal{D}$.

Let us introduce the following definitions.

Definition 3: Given a node v_i, its KR r_i, and a destination node v_d, a *loop-free forwarding rule* $\mathcal{F}$ associates the node v_i with another node v_k in $\mathcal{V} \setminus \{v_i\}$, in such a way that the path $\{v_i, v_k, \ldots, v_d\}$ obtained by applying the rule from source to destination is composed of distinct nodes.

We indicate with $v_k = l_{v_i}^{\mathcal{F}}(v_d, r_i)$ that v_k is the *next hop* of node v_i toward v_d with KR r_i, according to $\mathcal{F}$. Note that for the sake of simplicity, we will also refer to a generic node v_k as k, and omit the index $\mathcal{F}$. Thus, $l_{v_i}^{\mathcal{F}}(v_d, r_i)$ is referred to as $l_i(d, r_i)$.

Given the array $\underline{\mathbf{R}}$ of the KRs of all nodes, the rule $\mathcal{F}$ induces *paths* among any possible source-destination pair in the network. Thus

$$\mathcal{F} : \underline{\mathbf{R}} \rightarrow \mathbf{x}_{\mathbf{ij}}^{\mathbf{sd}}(\underline{\mathbf{R}}) \tag{1}$$

where $\mathbf{x}_{\mathbf{ij}}^{\mathbf{sd}}(\underline{\mathbf{R}}) = 1$ iff the link between node i and node j is part of the path between node s and node d with the given choice $\underline{\mathbf{R}}$ of ranges, when we apply the forwarding rule $\mathcal{F}$.

B. Energy Model

An accurate model for the energy consumption per bit at the physical layer is

$$E = E_{\text{elec}}^{\text{trans}} + \beta d^{\alpha} + E_{\text{elec}}^{\text{rec}} \tag{2}$$

where $E_{\text{elec}}^{\text{trans}}$ is the distance-independent amount of energy consumed by the transmitter electronics (PLLs, VCOs, bias currents) and digital processing, $E_{\text{elec}}^{\text{rec}}$ is the energy utilized by receiver electronics, while βd^{α} accounts for the radiated power necessary to transmit over a distance d between source and destination.

As in [26], we assume that

$$E_{\text{elec}}^{\text{trans}} = E_{\text{elec}}^{\text{rec}} = E_{\text{elec}}. \tag{3}$$

Hence, the overall expression for E in (2), which we refer to as *link metric* hereafter, simplifies to

$$E = 2 \cdot E_{\text{elec}} + \beta d^{\alpha}. \tag{4}$$

According to this link metric, the *topology information cost for node* v_i is expressed as

$$C_i^{\text{INF}}(r_i) = \Bigg[L_D \cdot \beta r_i^{\alpha} + (N_i(r_i) + 1) \cdot L_D \cdot E_{\text{elec}} + \sum_{m \in \zeta_i(r_i)} L_U \cdot \beta d_{mi}^{\alpha} + 2N_i(r_i) \cdot L_U \cdot E_{\text{elec}} \Bigg] \cdot \frac{1}{T_M} \tag{5}$$

where

α	path loss $(2 \leq \alpha \leq 5)$;
β	constant [Joule/(bit $\cdot$ m$^{\alpha}$)];
L_D	length of an ND-packet [bit];
L_U	length of an LU-packet [bit];
E_{elec}	energy needed by the transceiver circuitry to transmit or receive one bit [Joule/bit];
$N_i(r_i)$	number of neighbors of node i when its knowledge range is r_i;
$\zeta_i(r_i)$	set containing the indexes of the nodes in range r_i of node i;
T_M	period between two consecutive neighborhood discovery messages $[s]$.

The expression βr_i^{α} represents the energy needed to transmit one bit at distance r_i; thus, $L_D \cdot E_{\text{elec}} + L_D \cdot \beta r_i^{\alpha}$ is the energy needed for node i to transmit the ND-packet to all nodes in its knowledge range, where as each of the $N_i(r_i)$ nodes in its KR "spends" $L_D \cdot E_{\text{elec}}$ to receive the ND-packet. By adding these two components, we obtain the first line of (5). Then, each of the $N_i(r_i)$ nodes transmits an LU-packet. The energy expenditure has again a constant factor, $L_U \cdot E_{\text{elec}}$, plus a factor, $L_U \cdot \beta d_{mi}^{\alpha}$, which depends on the distance between the transmitting node v_m and node v_i. Moreover, v_i spends $L_U \cdot E_{\text{elec}}$ to receive each of the $N_i(r_i)$ LU-packets. By adding all these components, and dividing by T_M, which is the inverse of the location update frequency, we obtain the final expression for C_i^{INF}. In other words, C_i^{INF} is the *average energy* needed for node v_i to obtain topology information within range r_i.

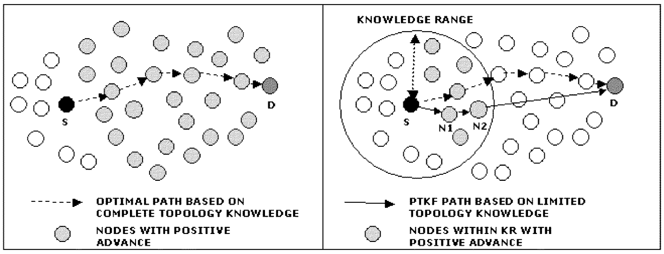
The *communication cost for node* v_i can be expressed as

$$C_i^{\text{COM}}(\underline{\mathbf{R}}) = \sum_{(s,d) \in \Pi_i(\underline{\mathbf{R}})} [\beta d_{il_i(d,r_i)}^{\alpha} + 2 \cdot E_{\text{elec}}] \cdot p_{sd} \tag{6}$$

with

$$\Pi_i(\underline{\mathbf{R}}) = \{(s, d) \text{ s.t. } x_{ij}^{sd} = 1 \text{ for at least one } j\}. \tag{7}$$

The set $\Pi_i(\underline{\mathbf{R}})$ contains all source-destination pairs whose path includes v_i as a transit node, as well as those for which v_i is the source. Thus, in (6), we sum over all the connections, where v_i is a transmitting node. Note that each term has a distance-independent component $2 \cdot E_{\text{elec}}$ (the energy needed to transmit and



(a) (b)

Fig. 4. Partial topology knowledge forwarding (PTKF)

receive 1 bit), and a distance dependent component $d^{\alpha}_{il_i(d,r_i)}$, which represents the αth power of the distance between nodes v_i and $v_{l_i(d,r_i)}$, this last being the next hop of v_i toward v_d when its KR is r_i. Every term is then multiplied by the average bit rate of the communication p_{sd}. Thus, $C_i^{\text{COM}}(\underline{\mathbf{R}})$ represents the *average energy* expenditure for all the communications node v_i is involved in. We can now state the *total cost for node* v_i as

$$C_i^{\text{TOT}}(\underline{\mathbf{R}}) = C_i^{\text{COM}}(\underline{\mathbf{R}}) + C_i^{\text{INF}}(r_i) \qquad \forall i \in \mathcal{V}. \tag{8}$$

Note that while the information cost of each node only depends on its own KR, the communication cost depends on the KRs of all nodes involved in the communication process.

C. Partial Topology Knowledge Forwarding (PTKF)

We now introduce a novel forwarding scheme, called partial topology knowledge forwarding (PTKF). PTKF can be classified as a *localized shortest weighted path* routing scheme with a *power* link metric, where routes are calculated based only on a limited local knowledge of the overall topology.

Let us refer to Fig. 4 and consider a node that is holding a message (S) and is in charge of forwarding it to a given destination node (D). If S had a complete topological view, it could calculate the optimal path toward the destination, i.e., the shortest weighted path that coincides with the minimum energy path when we consider a link metric of $2 \cdot E_{\text{elec}} + \beta d^{\alpha}$, according to (4). This is shown in Fig. 4(a), where the topological view of node S is constituted by all nodes of the network with positive advance (see Definition 2) with respect to the destination (grey nodes).

Conversely, in PTKF we assume that, given a limited KR, S only knows the position of all nodes inside this range and the position of the destination node. The topological view of S is constituted by node D and by all the nodes in the KR with positive advance with respect to D [see Fig. 4(b)]. In this case, the minimum energy path toward the destination is calculated only based on this limited topological view, i.e., the shortest weighted path only takes into account nodes in the KR and the destination, as the other nodes are unknown to S. It is assumed that nodes on the border of the KR can reach the destination node directly in one hop, e.g., node N_2 in Fig. 4(b) can directly reach D. Hence, we consider a fine grained topology close to the node holding the message (within the KR), and an extremely coarser grained topology outside (only the position of the destination node is considered). Thus, S will forward the message to the first node N_1 on the minimum energy path calculated in this way. In its turn, N_1 calculates the path toward the destination D, but this time according to its own KR. This can actually result in a different path being chosen by N_1 as compared with the path originally calculated by S.

Note that, unlike the forwarding schemes described in Section II-A, PTKF is not a greedy scheme. This scheme becomes more localized when the KR of each node gets smaller. We will show in the following that "small" KRs are chosen when energy efficiency is the major concern.

IV. Integer Linear Programming (ILP) Formulation

As stated above, our objective is selecting the vector $\underline{\mathbf{R}}$ of KRs which minimizes the energy expenditure of the overall network, given the set of connections $\mathcal{P}$ and a forwarding rule $\mathcal{F}$

$$\min_{\underline{\mathbf{R}}} C^{\text{TOT}} = \sum_{i \in \mathcal{V}} (C_i^{\text{COM}}(\underline{\mathbf{R}}) + C_i^{\text{INF}}(r_i)). \tag{9}$$

We refer to this problem as *optimal topology knowledge range* problem and formulate it as an ILP.

We consider discrete values of the KRs. The granularity of this quantization can be whatever, but obviously finer-grained transmission ranges increase the size of the space of possible solutions, thus making it harder to find the optimal values. Each variable $r_i, 0 \leq r_i \leq r^{max}$ assumes one out of k_{max} discrete, equidistant values in the set $\{r^0, r^1, \ldots, r^{k_{\max}-1}\}$, with $r^k - r^{k-1} = \Delta r$, $\forall k\, s.t.\, 1 \leq k \leq k_{\max}-1$, with $r^0 = 0$ and $r^{max} = r^{k_{max}-1}$. We refer to the set of indices $\{0, 1, \ldots, k_{\max} - 1\}$ as $\mathcal{R}$.

We introduce the following notations and variables:

$r(k)$ kth KR;

$r^{\alpha}(k)$ αth power of the kth KR;

$N_i(k)$ number of neighbors for node v_i when it selects the kth KR;

$f^{ij}_{dk} = 1$ iff, according to $\mathcal{F}$, node v_j is the next hop for node v_i, when v_d is the destination, and the kth range is chosen;

$a^k_{ij} = 1$ iff node v_j is in the kth KR of node v_i;

d^{α}_{ij} αth power of the distance between nodes v_i and v_j.

We introduce the following routing variables:

$x^{sd}_{ij} = 1$ iff link (i, j) is part of the path between v_s and v_d.

The assignment variables are the following:

$y^k_i = 1$ iff node v_i uses kth KR. We refer to the variables y^k_i as *knowledge range indices*.

We can now express the problem as the following.

Optimal topology knowledge range problem

Minimize

$$C^{\text{TOT}} = \sum_{i \in \mathcal{V}} \left(C_i^{\text{COM}} + C_i^{\text{INF}}\right) \tag{10}$$

Subject to

$$\sum_{k \in \mathcal{R}} y^k_i = 1 \quad \forall i \in \mathcal{V} \tag{11}$$

$$\sum_{j \in \mathcal{V}} \left(x^{sd}_{sj} - x^{sd}_{js}\right) = 1 \quad \forall s \in \mathcal{S} \quad \forall d \in \mathcal{D}\, \text{s.t.}\, s \neq d \tag{12}$$

$$\sum_{j \in \mathcal{V}} \left(x^{sd}_{dj} - x^{sd}_{jd}\right) = -1 \quad \forall s \in \mathcal{S} \quad \forall d \in \mathcal{D}\, \text{s.t.}\, s \neq d \tag{13}$$

$$\sum_{j\in\mathcal{V}}\left(x_{ij}^{sd}-x_{ji}^{sd}\right)=0 \quad \forall s\in\mathcal{S} \quad \forall d\in\mathcal{D}$$
$$\forall i\in\mathcal{V}\ \text{s.t.}\ s\neq d, i\neq s, i\neq d \quad (14)$$
$$x_{ij}^{sd}\leq\sum_{k\in\mathcal{R}}\left(y_i^k\cdot f_{dk}^{ij}\right) \quad \forall s\in\mathcal{S} \quad \forall d\in\mathcal{D}$$
$$\forall i,j\in\mathcal{V} \quad (15)$$
$$x_{sj}^{sd}=\sum_{k\in\mathcal{R}}\left(y_s^k\cdot f_{dk}^{sj}\right) \quad \forall s\in\mathcal{S} \quad \forall d\in\mathcal{D}$$
$$\forall j\in\mathcal{V}\ \text{s.t.}\ s\neq d \quad (16)$$
$$\begin{aligned}C_i^{\mathrm{INF}}=&\Bigg[L_N\cdot\beta\cdot\sum_{k\in\mathcal{R}}\left(y_i^k\cdot r^{\alpha}(k)\right)\\&+\left(\sum_{k\in\mathcal{R}}\left(y_i^k\cdot N_i(k)\right)+1\right)\cdot L_N\cdot E_{\mathrm{elec}}\\&+\sum_{m\in\mathcal{V}}\left(L_U\cdot\beta\cdot d_{mi}^{\alpha}+2\cdot L_U\cdot E_{\mathrm{elec}}\right)\\&\cdot\sum_{k\in\mathcal{R}}\left(y_i^k\cdot a_{im}(k)\right)\Bigg]\cdot\frac{1}{T_M} \quad \forall i\in\mathcal{V}\end{aligned} \quad (17)$$
$$\begin{aligned}C_i^{\mathrm{COM}}=&\sum_{s\in\mathcal{S}}\sum_{d\in\mathcal{D}}\sum_{j\in\mathcal{V}}\left(x_{ij}^{sd}\cdot p^{sd}\right.\\&\left.\cdot\left(2\cdot E_{\mathrm{elec}}+\beta\cdot d_{ij}^{\alpha}\right)\right), \quad \forall i\in\mathcal{V}.\end{aligned} \quad (18)$$

Constraint (11) imposes the existence of a single KR index different from zero for each node. Constraints (12)–(14) express conservation of flows [27], while constraints (15) and (16) impose that paths are built according to the forwarding rule defined by the input parameters f_{dk}^{ij}. Finally, constraints (17) and (18) express the information and communication cost with the KR index notation, respectively. Note that given a forwarding rule $\mathcal{F}$, expressed by the f_{dk}^{ij} parameters, the assignment of the routing (x_{ij}^{sd}) variables is completely dependent on the choice of KRs (y_i^k variables). Once the values of the y_i^k variables have been selected, the set $\mathcal{X}=\{x_{ij}^{sd}\}$ defines the path from source to destination for any connection in $\mathcal{P}$.

V. PRADA: A Distributed Protocol for Topology Knowledge Range Adjustment

The solution of the ILP problem is not feasible in a practical setting due to its complexity and centralized nature. Hence, we introduce PRADA, which determines the KRs online in a distributed way. The objective of PRADA is to allow network nodes to select stable and efficient topology KRs. This global target is achieved through distributed decisions and by means of probe packets exchanged among the nodes. The main idea behind PRADA is to allow each node to adjust its KR according to the feedback information it receives from neighboring nodes involved in the same multihop connections. In Section VI, we will show that PRADA quickly converges to a near-optimal solution.

To tradeoff between the topology information cost and the communication cost, each node that is part of the path of a particular connection (as a source or a transit node), periodically probes its possible KRs. Thus, the node is able to associate an increase/decrease in the overall energy expenditure to each KR. To clearly understand the rationale behind PRADA, we point out that while the information cost of each node only depends on its KR, the communication cost depends on the KRs of all nodes involved in the communication process. Thus, the communication cost must be monitored with probe packets.

PRADA is executed at each node v_i that has an active role in the network as a source or a transit node. We indicate as $\mathcal{P}_i$ the set of connections where v_i has an active role. Periodically, each active node selects a certain KR to be probed, different from the current one, in the discrete set of possible KRs. We refer to the selected KR as r_{probe} and to the current KR as r_{current}. For each connection $p\in\mathcal{P}_i$, v_i selects the next hop $l_{v_i}^{\mathcal{F}}(v_d^p, r_{\mathrm{probe}})$, where v_d^p is the destination node of the connection $p\in\mathcal{P}_i$, according to the forwarding rule $\mathcal{F}$ and to its current KR. The node calculates

$$C_i^{\mathrm{TOT}}(r_{\mathrm{probe}})=C_i^{\mathrm{INF}}(r_{\mathrm{probe}})+\sum_{p\in P_i}c_i^p(r_{\mathrm{probe}}) \quad (19)$$

where $c_i^p(r_{\mathrm{probe}})$ is the cost of the transmissions along the path from v_i to the destination of the connection p, with KR r_{probe}. This accounts for the cost of transmitting data from the node itself to all the destinations, plus the cost of information associated to the new KR r_{probe}.

If $C_i^{\mathrm{TOT}}(r_{\mathrm{probe}})<C_i^{\mathrm{TOT}}(r_{\mathrm{current}})$, the value of the KR is updated $(r_{\mathrm{current}}=r_{\mathrm{probe}})$.

A probe packet has five data fields. The first two fields contain the geographical coordinates of the source and the destination. The third contains a parameter called *cumulative communication cost* and the fourth contains the value r_{probe} of KR. The last field is a 1-bit flag, which is equal to 1 if the packet is on the *forward* path toward the destination, or equal to 0 if it is on the *reverse* path. The cumulative communication cost field, initialized to 0 when the packet is created, is updated hop-by-hop by adding the *incremental communication cost*, i.e., the communication cost necessary to reach the next hop, to the communication cost stored in the packet. This way, partial cumulative communication costs are computed hop-by-hop along the path from the sender to the destination.

Algorithm 1 PRADA
begin
randomly select $r_{\mathrm{probe}}\neq r_{\mathrm{current}}$
for each $p\in\mathcal{P}_i$ **do**
  $v_i\rightarrow l_{v_i}^{\mathcal{F}}(v_d^p, r_{\mathrm{probe}})$: probe packet
end for
wait for return packets
$C_i^{\mathrm{TOT}}(r_{\mathrm{probe}})=C_i^{\mathrm{INF}}(r_{\mathrm{probe}})+\sum_{p\in P_i}c_i^p(r_{\mathrm{probe}})$
if $(C_i^{\mathrm{TOT}}(r_{\mathrm{probe}})<C_i^{\mathrm{TOT}}(r_{\mathrm{current}}))$ **then**
  $r_{\mathrm{current}}=r_{\mathrm{probe}}$
end if
end

After choosing a KR r_{probe}, for each connection in $\mathcal{P}_i$ the node sends a probe packet to the relevant next hop and waits for its return. When a node receives a probe packet on the forward path, it looks into a cost record table to check if it already knows the incremental communication cost needed to reach this destination. If it does, there is no need to forward the probe packet to the destination. The probe packet is sent back with the updated information and the path bit is set to *reverse*. If it does

TABLE I
PARAMETERS OF THE MODEL USED FOR SIMULATIONS

	Scenario 1	**Scenario 2**	**Scenario 3**
Size	$(10mx10m)$	$(10mx10m)$	$(50mx50m)$
KRs	$(0,2,4,6,8)m$	$(0,2,4,6,8)m$	$(0,4,..,20)m$
α	4	3	*varies*
L_D	$128bits$	$128bits$	$128bits$
L_U	$128bits$	$128bits$	$128bits$
T_M	$1s$	*varies*	$0.1s$
E_{elec}	*varies*	$50pJ/bit$	$5nJ/bit$
β	$100pJ/bit/m^{\alpha}$	$100pJ/bit/m^{\alpha}$	$100pJ/bit/m^{\alpha}$
Rates	$10kbit/s$	$100kbit/s$	$100kbit/s$

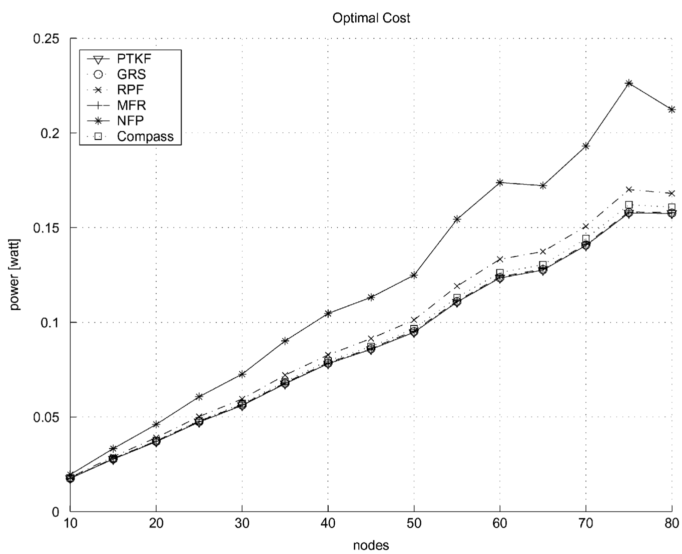


Fig. 5. Scenario 1—Optimal cost for the implemented forwarding schemes, $E_{\text{elec}} = 50 \cdot 10^{-9}$ J/bit.

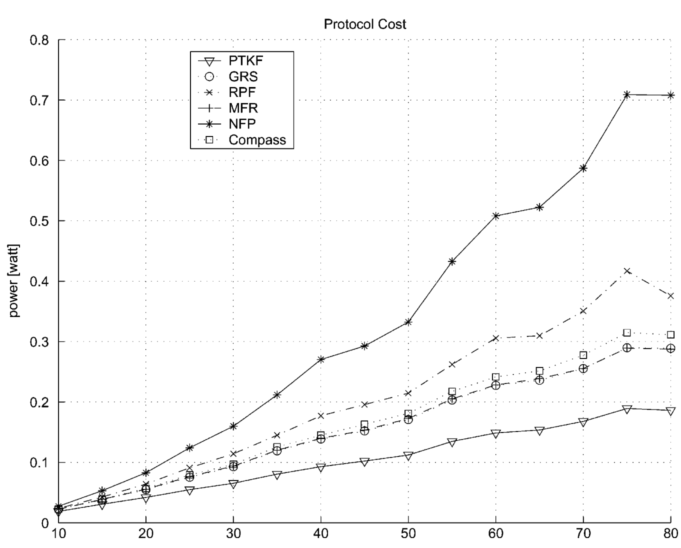


Fig. 6. Scenario 1—Cost with PRADA for the implemented forwarding schemes, $E_{\text{elec}} = 50 \cdot 10^{-9}$ J/bit.

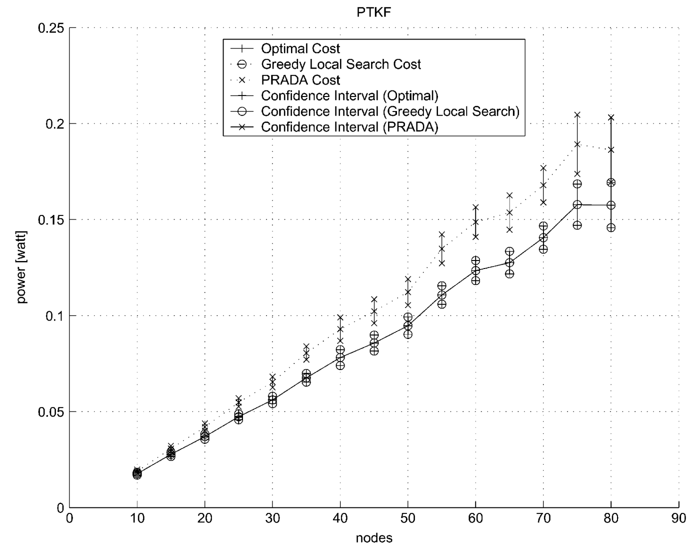


Fig. 7. Scenario 1—Comparison of optimal cost for PTKF with different approaches, $E_{\text{elec}} = 50 \cdot 10^{-9}$ J/bit.

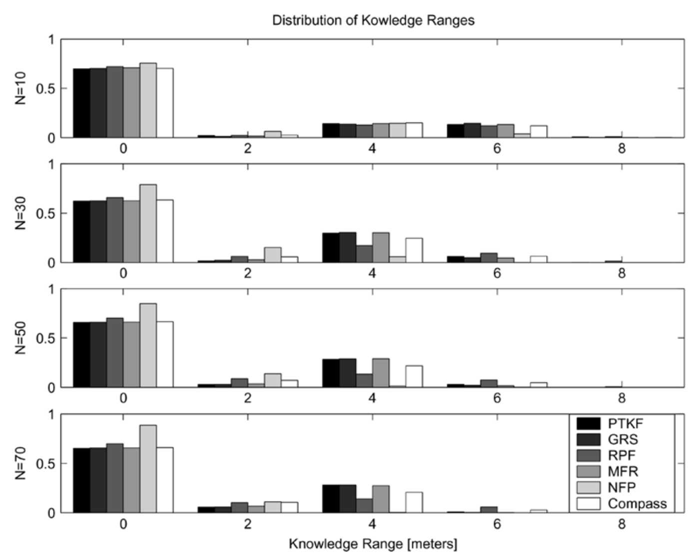


Fig. 8. Scenario 1—Distribution of values of knowledge range, $E_{\text{elec}} = 50 \cdot 10^{-9}$ J/bit.

not, the packet is forwarded to the next hop toward the destination in order to evaluate the communication cost. The packet is forwarded until a node with information for that destination or the destination itself is reached. When a node has gathered all the cost information associated to a certain r_{probe}, it calculates the cost associated to r_{probe} as in (19). Algorithm 1 describes the operations performed by a node v_i which executes PRADA.

In order to reach stability, the KR is updated only if the moving average of the communication cost for the last N_{probe} values gathered is lower than the cost of the current range. In the experiments, we assume that all the KRs are probed with the same probability. More sophisticated strategies can also be implemented in order to selectively scan the KRs, aimed at saving transmission power, e.g., by avoiding values of KR that are not likely to bring any benefit.

VI. PERFORMANCE EVALUATION

We implemented the forwarding schemes described in Section II-A, PTKF given in Section III-C and PRADA, given in Section V in a simulator. We further implemented the ILP problem in AMPL [28] and solved it with CPLEX [29].

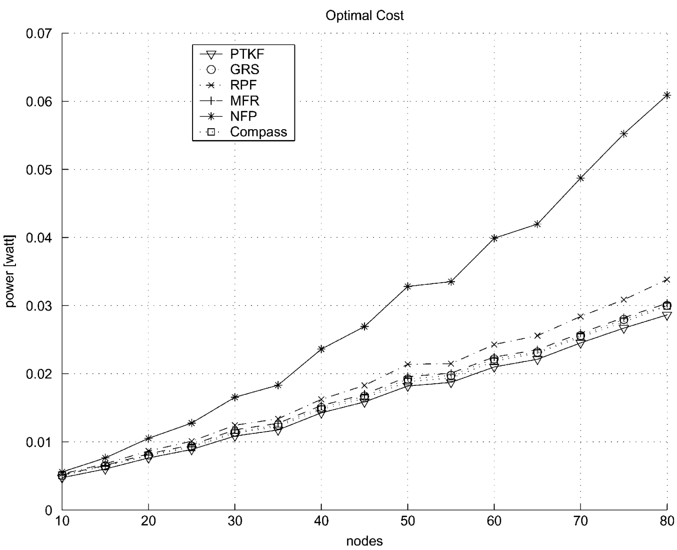


Fig. 9. Scenario 1—Optimal cost for the implemented forwarding schemes, $E_{\mathrm{elec}} = 50 \cdot 10^{-10}$ J/bit.

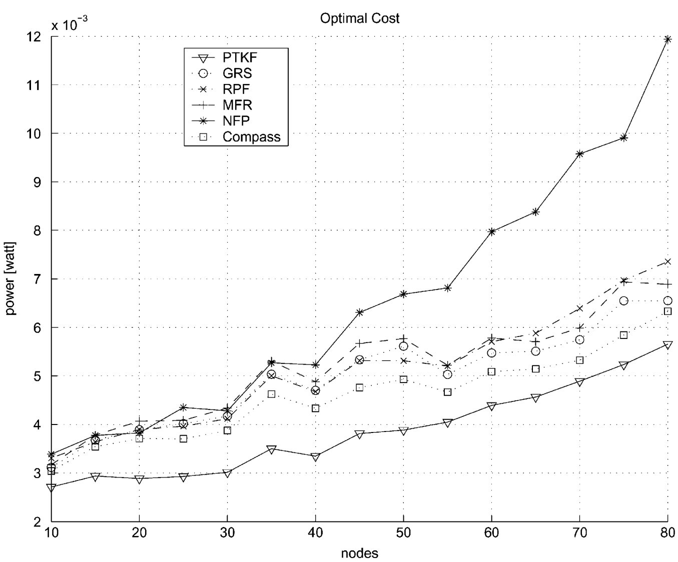


Fig. 10. Scenario 1—Optimal cost for the implemented forwarding schemes, $E_{\mathrm{elec}} = 50 \cdot 10^{-11}$ J/bit.

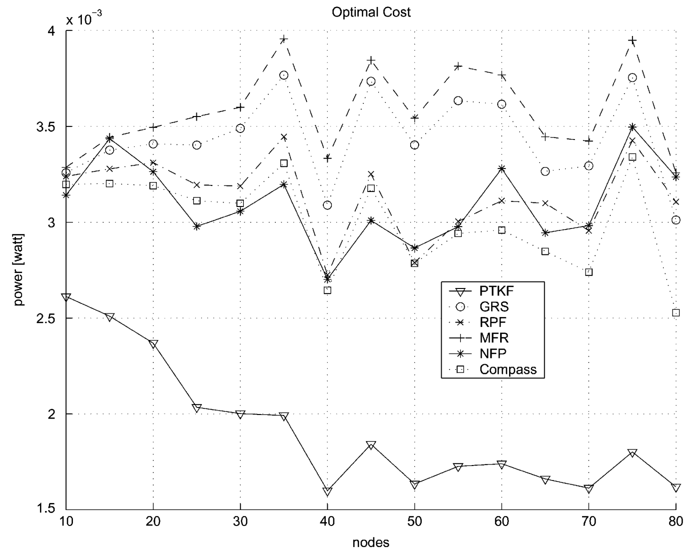


Fig. 11. Scenario 1—Optimal cost for the implemented forwarding schemes, $E_{\mathrm{elec}} = 50 \cdot 10^{-12}$ J/bit.

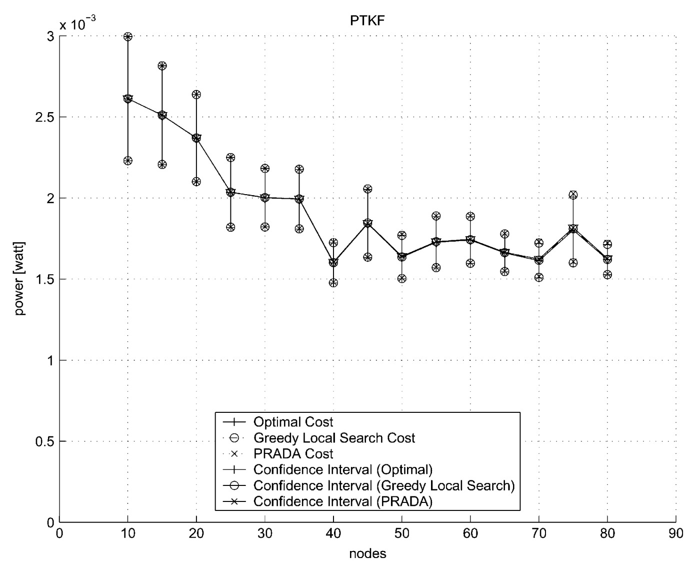


Fig. 12. Scenario 1—Comparison of optimal cost for PTKF with different approaches, $E_{\mathrm{elec}} = 50 \cdot 10^{-12}$ J/bit.

We are particularly interested in scenarios where the density of nodes is high, such as those encountered in sensor network applications. However, due to the computational complexity of the problem, and to the large amount of the input data, a state-of-the-art workstation can find the optimal solution with CPLEX for networks with at most 100 nodes. Thus, we consider small geographical areas in order to take into account the effects of high node densities on the problem. The model depends on several input parameters, and on the appropriate choice of these parameters, which are highly dependent on the technology and on the target applications. Our choice for these parameters was motivated by the model presented in [26]. However, we also vary these parameters in order to study their relevant effects on the network performance.

We present simulation results for the scenarios illustrated in Table I. In Scenario 1, nodes are randomly deployed in a 10 m $\times$ 10 m terrain. All nodes are sources with 10 kbit/s flows directed toward a single sink node. In Fig. 5, we show the optimal cost [the minimum of the objective function of the optimal KR problem, stated in (10)], with increasing number of nodes for all the implemented forwarding schemes (Sections II-A and III-C). The value chosen for the parameter E_{elec} is $50 \cdot 10^{-9}$ J/bit [26]. Note that confidence intervals are not shown for the sake of clarity. Since the area of the terrain is very small, multihop paths are often not energy efficient, which leads source nodes to directly transmit to the destination without relying on intermediate forwarding nodes. For this reason, different forwarding schemes show similar performance. In Fig. 6, we show the total cost for all the implemented forwarding schemes in Scenario 1, obtained by applying PRADA with $N_{\mathrm{probe}} = 3$.

In Fig. 7, we compare the optimal cost obtained for PTKF with three different approaches for the solution of the optimization problem, with 95% confidence intervals. The problem is solved with CPLEX (optimal solution), with a greedy local

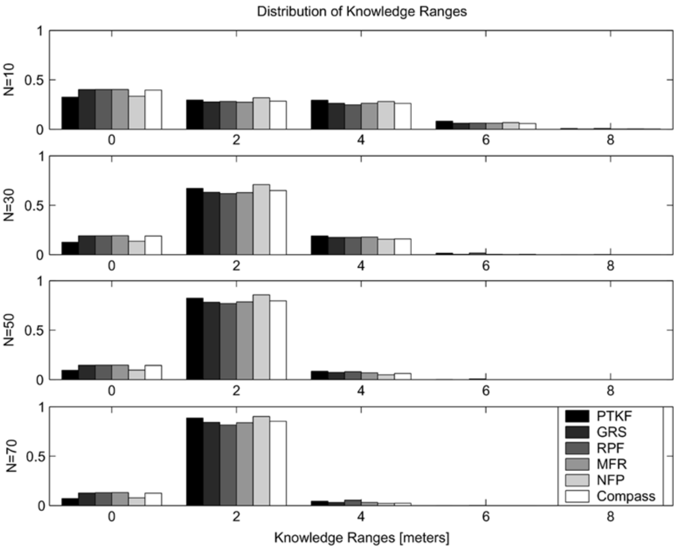


Fig. 13. Scenario 1—Distribution of values of knowledge range, $E_{\mathrm{elec}} = 50 \cdot 10^{-12}$ J/bit.

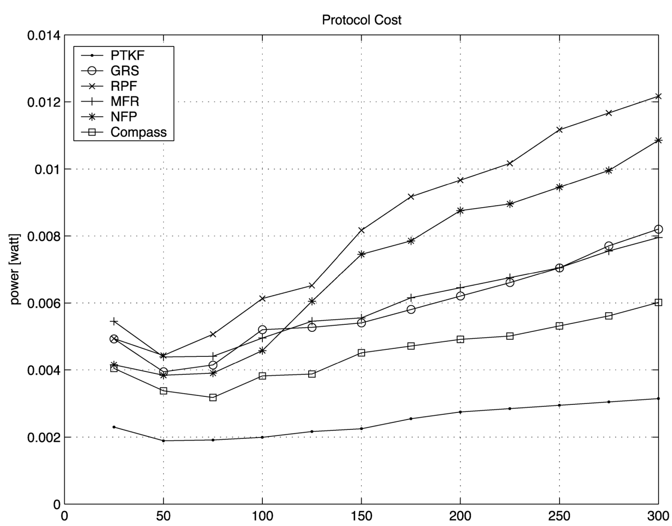


Fig. 14. Scenario 1—Cost with PRADA for the implemented forwarding schemes, $E_{elec} = 50 \cdot 10^{-12}$ J/bit.

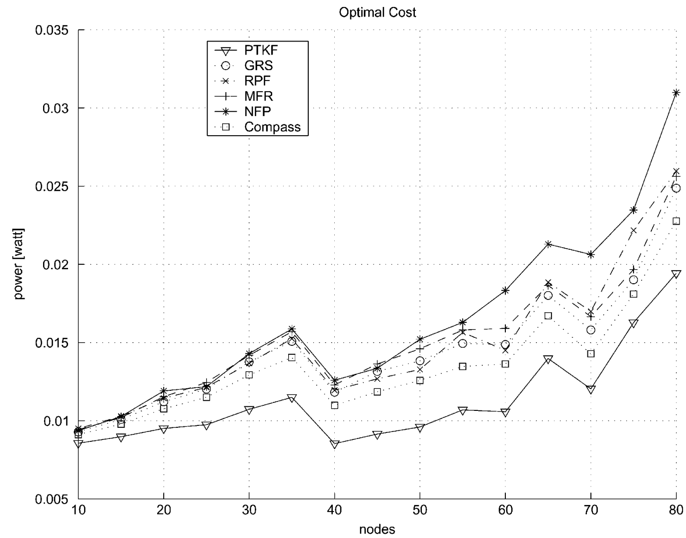


Fig. 15. Scenario 2—Optimal cost for the implemented forwarding schemes, $T_M = 0.01$ s.

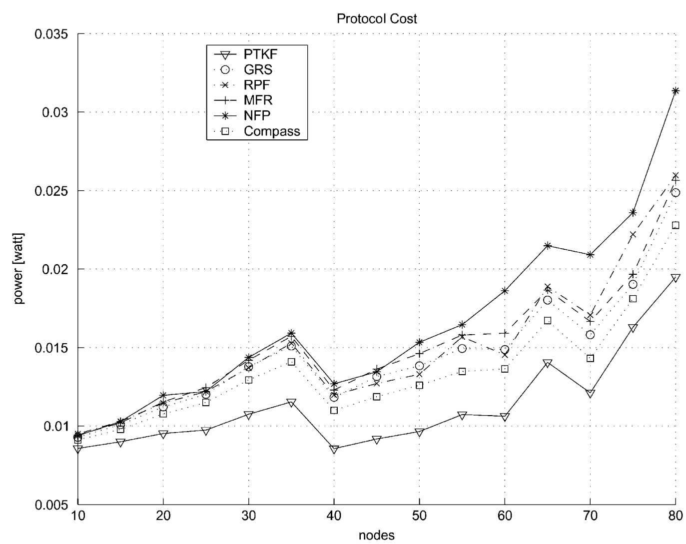


Fig. 16. Scenario 2—Cost with PRADA for the implemented forwarding schemes, $T_M = 0.01$ s.

search heuristic, and by applying the PRADA distributed protocol. CPLEX finds the optimal solution for mixed integer problems by using a branch and bound algorithm. The greedy local search heuristic scans the nodes one after another and selects for each of them the KR which minimizes the cost; the process is repeated periodically until stability is reached. The PRADA curve is very close to the CPLEX and the greedy local search heuristic curves. This behavior, as will be shown, becomes more evident when the problem becomes more localized, i.e., when multihop paths are more energy efficient.

In Fig. 8, we show the distribution of the values of the KRs in Scenario 1, with $N = 10, 30, 50$, and 70 nodes. In this scenario, the average KR is below 1.5 m, and as can be seen most nodes either have a KR equal to 0 (i.e., they "prefer" to know nothing about their neighborhood and directly transmit to the destination) or they try to know "far" nodes (4, 6 m) to use them as intermediate relays. As a result, it is either efficient to directly transmit to destination or use at most one intermediate node as relay.

By decreasing the E_{elec} parameter, we decrease the weight of the component in energy expenditure [link metric in (4)] which is independent of the distance. Hence, it becomes more energy efficient to select multihop paths, since the overall distance independent part of the energy expenditure increases with the number of hops. We would obtain the same effect by increasing the area of the terrain, but we would have a less dense deployment.

It can be inferred by comparing Figs. 5 and 9–11 that the more multihop paths are energy efficient (low values for E_{elec}), the more PTKF (Section III-C) outperforms the other schemes. When "long" paths are energy efficient, PTKF takes a better advantage of the local knowledge of the neighborhood. In Figs. 5 and 9–11, the values for E_{elec} are $50 \cdot 10^{-9}, 50 \cdot 10^{-10}, 50 \cdot 10^{-11}$, and $50 \cdot 10^{-12}$ J/bit, respectively.

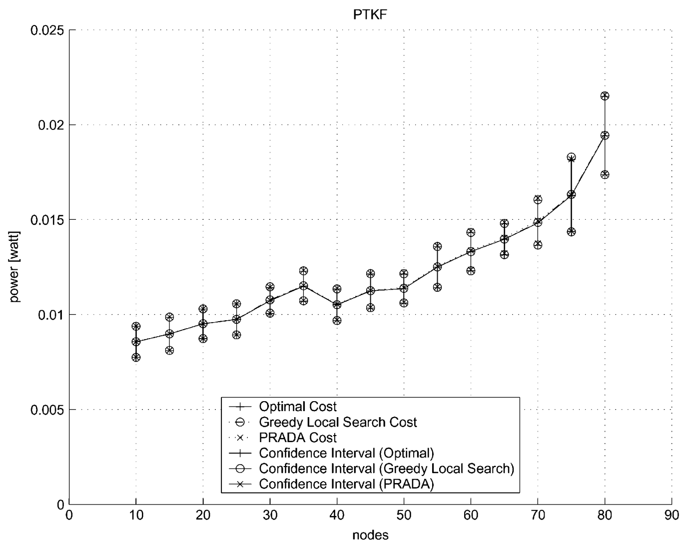


Fig. 17. Scenario 2—Comparison of optimal cost for PTKF with different approaches, $T_M = 0.01$ s.

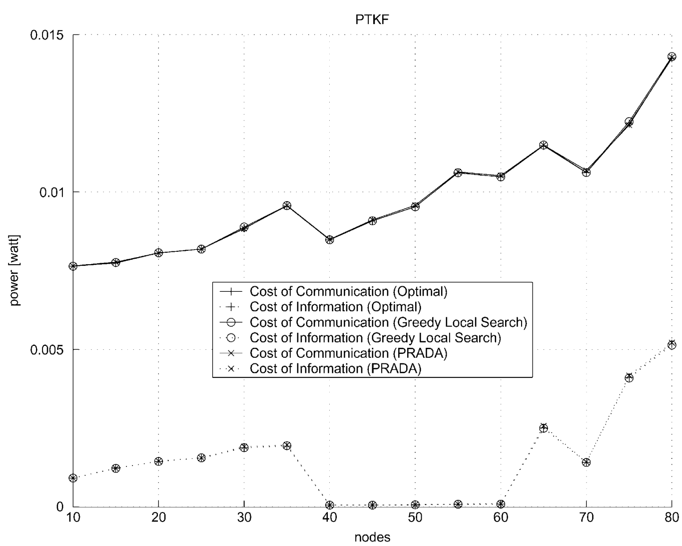


Fig. 18. Scenario 2—Information cost and communication cost for PTKF, $T_M = 0.01$ s.

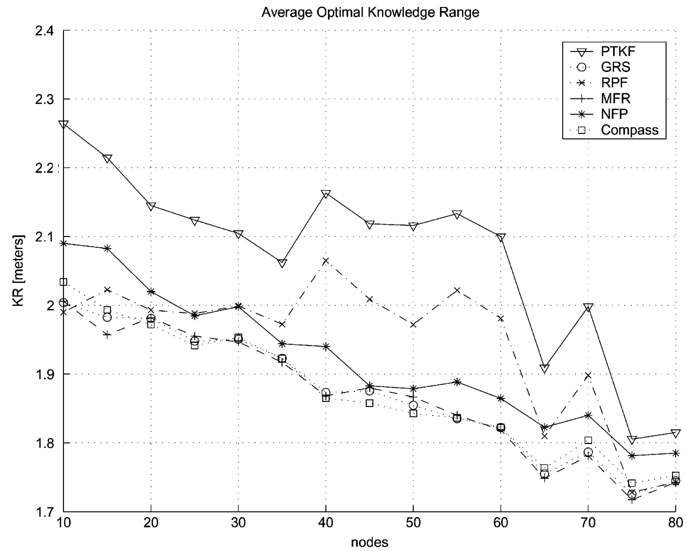


Fig. 19. Scenario 2—Average KR with different forwarding schemes, $T_M = 0.01$ s.

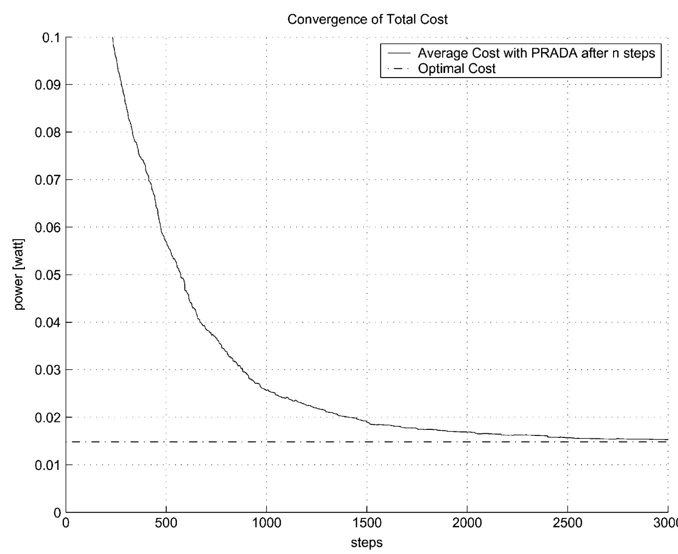


Fig. 20. Scenario 2—Convergence of PRADA with PTKF, 70 nodes, and $T_M = 0.01$ s.

For $E_{\text{elec}} = 50 \cdot 10^{-12}$ J/bit, the cost obtained with PRADA is optimal, as can be seen from Fig. 12. When the distance independent term E_{elec} in (4) becomes small as compared with the area of the terrain, multihop paths become more energy efficient. When this occurs, by selecting KRs which are optimal only locally, as PRADA does, we obtain globally optimal solutions, because the problem becomes more localized when E_{elec} decreases. In Fig. 13, we show that it is more energy efficient to select close nodes as next hop (KRs are 2 m), as E_{elec} decreases. This is particularly true when the density increases. Furthermore, as shown in Fig. 14, when the density increases, not only PTKF outperforms the other schemes, but also the energy consumption increases slowly with increasing number of nodes (up to 300).

In Scenario 2, all nodes are sources with 100 kbit/s flows directed toward a single sink node. In Fig. 15, we report optimal costs with increasing number of nodes for all the implemented forwarding schemes (Section II-A). Again, PTKF performs better than the other forwarding schemes. More "greedy" schemes such as NFP and MFR are shown to consume more energy.

Fig. 16 shows the total cost in Scenario 2 for all the implemented forwarding schemes, obtained by applying PRADA with $N_{\text{probe}} = 3$. Figs. 15 and 16 are almost identical, which is explicitly shown by Fig. 17, where we compare the results obtained for PTKF with the three different optimization approaches (CPLEX, greedy local search, and PRADA). In Fig. 18, we depict the information cost (17) and the communication cost (18) for PTKF, again with the three different approaches. The communication cost is shown to highly exceed the information cost when relatively high data rate flows must be supported. In Fig. 19, we show the average value of the KR with increasing number of nodes for all the proposed schemes. It is shown that a very limited knowledge of the topology is needed in average, less than 2 m.

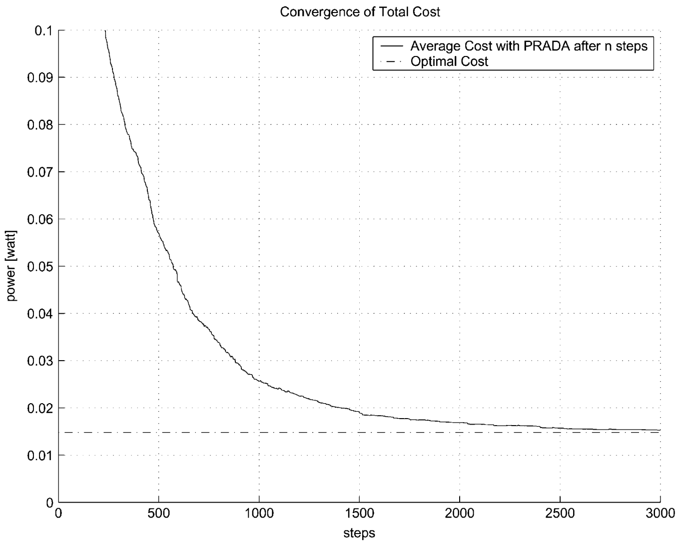


Fig. 21. Scenario 2—Convergence of PRADA with GRS, 40 nodes, and $T_M = 0.01$ s.

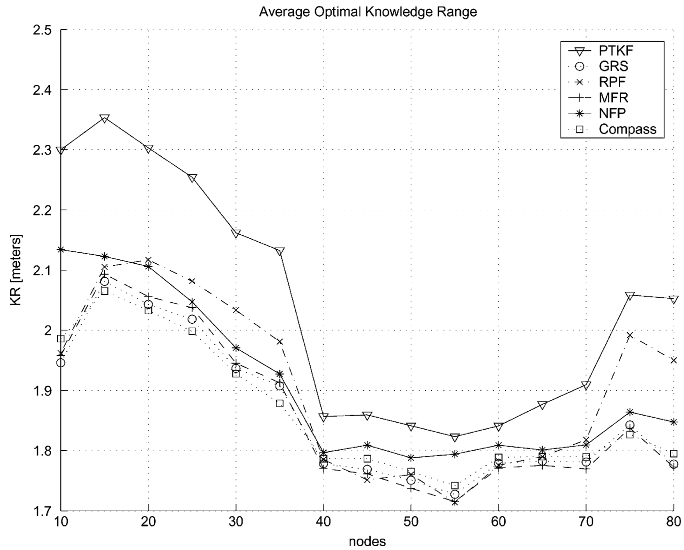


Fig. 23. Scenario 2—Average KR with different forwarding schemes, $T_M = 1$ s.

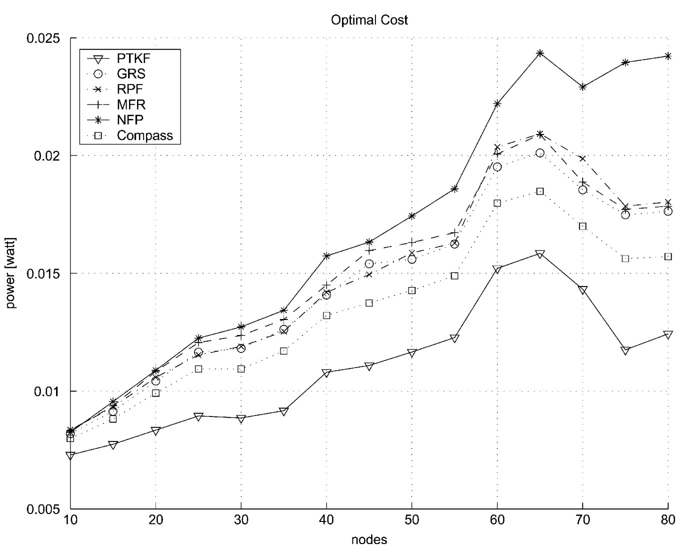


Fig. 22. Scenario 2—Optimal cost for the implemented forwarding schemes, $T_M = 1$ s.

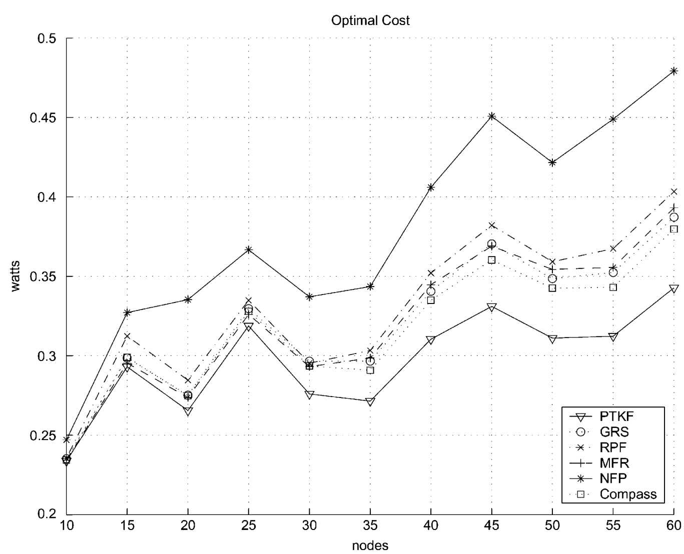


Fig. 24. Scenario 3—Optimal cost for the implemented forwarding schemes, $\alpha = 3$.

In Figs. 20 and 21, we show the average convergence dynamics of PRADA to the optimal solution with 70 and 40 nodes, respectively. At each *step*, one node randomly selects and probes one of its KRs. For 70 nodes, after 3000 steps, we obtain a near-optimal solution. In Fig. 22, we assume a lower location update frequency (higher T_M). Thus, we set $T_M = 1$. As can be seen in Fig. 22, for lower location update frequencies PTKF even more evidently outperforms the other schemes. A more extended local topology knowledge brings benefits in terms of energy to the scheme which best exploits this information. This is confirmed by Fig. 23 that shows how the average KRs increase in general, and particularly for PTKF which is able by its nature to better take advantage of a more extended knowledge. Still, the extension of local knowledge of the topology is very limited compared with the dimensions of the terrain.

In Scenario 3, we consider traffic patterns that are more likely encountered in an ad hoc network. In this case, 25% of the deployed nodes generate a 100 kbit/s traffic flow, each directed toward another randomly selected node. Figs. 24 and 25 report optimal cost with increasing number of nodes for all the implemented forwarding schemes, with $\alpha = 3$ and $\alpha = 4$, respectively. For high values of α the optimal cost decreases as the node density increases. Conversely, for low values of α the increased traffic overcomes the positive effect of a higher node density. As the number of nodes becomes higher, the cost of information and the optimal KRs increase with the overall effect of decreasing the optimal cost. Again, in all the experiments performed in Scenario 3, PTKF is shown to perform better than any other scheme, while more "greedy" schemes, such as NFP and MFR, are shown to lead to higher energy consumptions.

VII. Conclusion

We discussed how to determine optimal local topology knowledge for energy efficient geographical routing in ad hoc

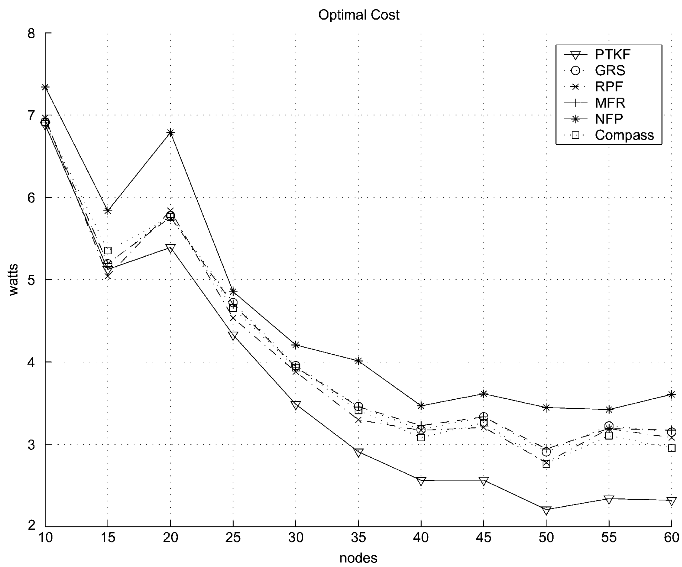


Fig. 25. Scenario 3—Optimal cost for the implemented forwarding schemes, $\alpha = 4$.

and sensor networks. We provided an ILP formulation of the problem which constitutes a framework for the analysis of the energy efficiency of different forwarding schemes. We introduced a new localized forwarding scheme for geographical routing, PTKF, and a distributed protocol for online knowledge range adjustment PRADA. PTKF is shown to outperform existing greedy forwarding schemes, and PRADA is shown to lead to near-optimal energy consumption. Furthermore, we demonstrated that only a limited local topology knowledge is needed to take energy efficient routing decisions. Future research will include the extension of the model, primarily to include features such as battery and bandwidth constraints for the nodes.

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