WIRELESS COMMUNICATIONS AND MOBILE COMPUTING
Wirel. Commun. Mob. Comput. 2013; **13**:424–438
Published online 8 February 2011 in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/wcm.1112

RESEARCH ARTICLE

Multi-cost routing for energy and capacity constrained wireless mesh networks

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ABSTRACT

We propose a class of novel energy-efficient multi-cost routing algorithms for wireless mesh networks, and evaluate their performance. In multi-cost routing, a vector of cost parameters is assigned to each network link, from which the cost vectors of candidate paths are calculated using appropriate operators. In the end these parameters are combined in various optimization functions, corresponding to different routing algorithms, for selecting the optimal path. We evaluate the performance of the proposed energy-aware multi-cost routing algorithms under two models. In the network evacuation model, the network starts with a number of packets that have to be transmitted and an amount of energy per node, and the objective is to serve the packets in the smallest number of steps, or serve as many packets as possible before the energy is depleted. In the dynamic one-to-one communication model, new data packets are generated continuously and nodes are capable of recharging their energy periodically, over an infinite time horizon, and we are interested in the maximum achievable steady-state throughput, the packet delay, and the energy consumption. Our results show that energy-aware multi-cost routing increases the lifetime of the network and achieves better overall network performance than other approaches. Copyright © 2011 John Wiley & Sons, Ltd.

KEYWORDS
wireless mesh networks; multi-cost routing; energy and capacity constraints

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1. INTRODUCTION

A node in a wireless mesh network consumes energy when transmitting, receiving or processing data, or when simply listening to the channel. Since wireless nodes are usually battery-operated, energy is a scarce resource limiting the performance and lifetime of the network, in addition to the interference and capacity constraints. In this work we study multi-cost routing strategies for wireless mesh networks that take into account energy-related parameters, such as the node residual energies, the node transmission powers, and the hop count. We focus on wireless mesh networks consisting of static nodes with finite energy reserves, even though our routing algorithms can also be extended to the case of *ad hoc* networks, using appropriate techniques to address mobility [1,2]. Energy charging is not always guaranteed in wireless mesh networks, either by design or due to other reasons.

We can distinguish between two routing approaches in wireless networks: in particular, the *single-cost* and the *multi-cost* routing approach. Most routing protocols proposed till date are based on the single-cost idea, where a single metric is used to represent the cost of using a link. This link metric can be a function of several network parameters (including load, energy and interference related parameters), but it is still a scalar. Routing algorithms of this kind calculate the path that has the minimum cost for each source–destination pair. Single-cost routing algorithms cannot optimize performance with respect to general cost functions, and they do not easily support Quality of Service (QoS) differentiation. Also, they usually yield only one path per source–destination pair, leading to non-uniform traffic distribution and possible instability problems [3].

In the multi-cost routing approach proposed in the current work, each link[†] is assigned a cost vector consisting

[†] The term ‘link’ is used to refer to a single-hop connection between neighboring nodes, while the term ‘path’ is used to refer to multi-hop connections between two nodes in the network.

of several cost parameters. Specifically, in our formulation for wireless networks, the cost parameters of a link $l = (i, j)$ include the hop count, the energy expended by the transmitting node i, and its residual energy. Other parameters of interest, such as the residual energy of the receiving node j, a measure of the interference caused to other nodes and links, the available link capacity, and others, can also be included in our formulation in a straightforward manner. A cost vector can then be defined for a path [3] by combining component-wise the cost vectors of its links according to some associative operator. The class of multi-cost routing algorithms that we propose consist of two phases: they first compute a set of candidate non-dominated paths for a given source–destination pair, and then they select the path that minimizes a desired optimization function. We will say that a path p_1 dominates another path p_2 that corresponds to the same source–destination pair if p_1 is better than p_2 with respect to all the cost parameters. Also, the function to be optimized is chosen based on the interests of the network, but it may also depend on the user QoS requirements or on the amount of data that has to be transferred. We should note that applying similar optimization functions using the single-cost approach would either be impossible (for nonlinear metrics) or would require (for linear metrics) the re-running of a minimum cost algorithm, using each time a corresponding link metric.

In this paper, we propose several multi-cost routing algorithms, each corresponding to a different choice for the optimization function used. The proposed algorithms are based on the multi-cost routing approach, according to which the set of candidate paths for each source–destination pair is first formed. The selection of the optimal path is then made based on the optimization function in use, thus resulting in a distinct routing strategy for each one of the proposed optimization functions. Different cost parameters, domination relations, and optimization functions represent distinct sets of routing decisions (routing algorithms). To the best of our knowledge, there are very few works (if any) that use multi-cost routing in wireless networks, while even in the wired networks literature, the majority of relevant works use multi-constrained routing.

Multi-cost routing can be considered as a generalization of *multi-constrained* routing considered in earlier works mainly in the context of wired networks. In the multi-constrained routing problem, a constraint is specified for each of the cost parameters of a path and the target is to find paths that satisfy all the constraints. In the multi-cost routing problem there are no hard constraints and the target is to find paths that are better than all other paths for *all* or *some* of the cost parameters, and select the one that is optimal with respect to the optimization function used. Multi-cost routing is, therefore, a generalization of multi-constrained routing, in the sense that the latter case can be obtained from the former case, by choosing the function to be optimized so as to have infinite cost at the constraint points.

We evaluate the proposed algorithms' performance for wireless mesh networks under two quite different models: the *network evacuation* and the *dynamic one-to-one communication* model. These models signify two distinct ways of network traffic generation. The network evacuation model is a model first proposed in the current paper and has not been used elsewhere, at least for mobile networks. The dynamic one-to-one model (or variations of it) has been used by several other authors in previous works for evaluating the performance of their proposed algorithms. In the network evacuation problem, where nodes do not have energy recharging capabilities, the network starts with a certain number of packets that have to be routed and a certain amount of energy per node, and the objective is to serve the packets in the smallest number of steps, or to serve as many packets as possible before the energy at the nodes is depleted. We find that by using appropriate energy-aware cost functions, energy consumption can be spread more evenly among the nodes, leading to longer lifetime for the network. Even though energy-aware routing may sometimes give longer paths than the minimum required, it is observed that in the long run, when nodes start running out of energy, it gives better overall performance results.

In the dynamic one-to-one communication problem (see Figure 1) packets with uniformly distributed destinations are generated at each network node according to a random process, and energy is also recharged at each node at a given rate, over an infinite time horizon. We examine theoretically the relative effects energy and capacity/interference constraints have on the performance of two-dimensional wireless mesh networks and calculate upper bounds on the maximum achievable throughput under these constraints. The results obtained show that the proposed multi-cost energy-aware algorithms outperform other algorithms, achieving larger maximum throughput $p_{\max}$ for all recharging rates tested, and smaller average packet delay for a given packet generation probability $p < p_{\max}$. We also find that the average delay increases more abruptly when the traffic load reaches its maximum limitation due to the energy constraint, while it increases more smoothly when the traffic reaches its maximum limitation due to the capacity/interference constraint.

The remainder of the paper is organized as follows. In Section 2 we report on previous work. In Section 3 we present multi-cost routing for a general network, while Section 4 describes cost parameters and optimization functions that are specific to wireless mesh networks. In Section 5 we evaluate the performance of the proposed routing algorithms under the network evacuation model. Beginning with Section 6, we turn our attention to the dynamic one-to-one communication model, and present upper bounds on the maximum achievable throughput of two-dimensional networks under capacity and energy limitations. In Section 7 we present simulation results on the performance of multi-cost routing under the dynamic one-to-one communication model. Finally, Section 8 concludes the paper.

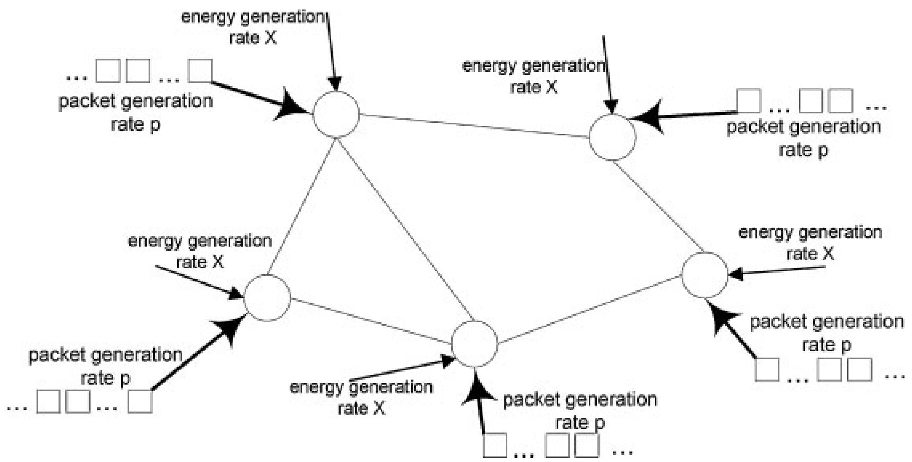

Fig. 1. The dynamic one-to-one communication model (infinite-time horizon problem). Packets with uniformly distributed destinations are generated at each node of the network with probability p during a slot. Energy is also generated at each node at a rate of X units of energy per slot. For a given network and energy generation rate X, we are interested in the maximum generation probability p for which the network is stable, and in the average packet delay for any load in the stability region.

2. PREVIOUS WORK

In general, mesh networks can be seen as a special case of *ad hoc* network, where nodes are usually static. A great deal of work on wireless *ad hoc* networks has focused on the design of efficient routing protocols. Energy-efficiency has been considered from the perspective of either minimizing the total energy consumption or maximizing the network lifetime [4]. Regardless of the methodology used, most energy-efficient protocols search for a path that minimizes an energy-related cost metric.

Towards the direction of maximizing network lifetime, Reference [5] proposes a protocol where the link costs are defined based on the initial and the current energy at the transmitting nodes, while Reference [6] presents an algorithm that excludes the energy starving nodes from route selection. In Reference [7], a cost metric is used for routing, which is a function of the remaining battery level and the number of neighbors of a node. Other works have focused on the discovery of energy efficient routes under the constraint of a fixed end-to-end bit error rate [8], or by considering the expected number of retransmissions for reliable packet delivery [9]. In Reference [10], the LEAR protocol is presented where a node decides to forward or not traffic based on its residual energy.

A protocol that minimizes the network energy consumption is presented in Reference [11], where the link costs are defined based on the energy expenditure for unit flow transmission. Reference [12] proposes two routing algorithms that adjust the node transmission power in order to reduce the energy expenditure. In another work [13], a distributed algorithm is presented that incorporates power control in the routing of packets, and tries to increase energy consumption at nodes with plenty of energy while reducing consumption at nodes with small energy reserves. Span [14] is a distributed, randomized algorithm where nodes make local decisions on whether to sleep, thus reducing energy consumption, or to join a backbone infrastructure.

Another series of works studies wireless mesh networks whose nodes are equipped with a solar panel enabling their recharging [15–18]. In References [19] and [20], the authors define the problem of determining and assigning to each node the right size of solar panel and battery. In Reference [21], a queuing analytical model is presented to investigate the performances of different sleep and wakeup strategies in a solar-powered wireless mesh network, while network models that assume energy recharging capabilities were considered in Reference [22]. In the present work we study the impact that the node recharging capability has on the performance limitations of the proposed multicost routing strategies.

The routing protocols mentioned above follow the single-cost approach, in the sense that they base their decisions on a single, scalar metric (which maybe a function of several metrics). Multi-constrained routing algorithms have also been investigated, especially for wired networks [23–26]. Finding paths subject to two or more cost parameters/constraints is in most cases an NP-complete problem [27,28]. As a result, most algorithms proposed in this area concentrate on solving the Multi-Constrained Path (MCP) problem or the Multi-Constrained Optimal Path (MCOP) problem in a heuristic and approximate way with polynomial and pseudo-polynomial-time complexities, paying little attention to the parameters/costs used and their effects on network performance. The multi-constrained problem has been less studied in the context of wireless *ad hoc* networks, even though these networks have important reliability, energy, and capacity constraints that are not present in wired networks. In Reference [29], the authors propose a probabilistic modeling of the link state for wireless networks, and propose an approximation of a local multipath

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DOI: 10.1002/wcm

routing algorithm to provide soft-QoS under delay and reliability constraints. In Reference [30], a multi-constrained QoS routing algorithm for mobile *ad hoc* networks is proposed that uses simulated annealing. In Reference [31], the authors present an algorithm based on depth-first-search that solves the general k-constrained MCP problem with pseudo-polynomial time complexity. In References [32] and [33], well-known routing algorithms for *ad hoc* networks are extended to support QoS through the usage of multiple constraints. These algorithms focus on the bandwidth and delay constrained routing problem. In Reference [34], a QoS routing scheme for *ad hoc* networks that uses flooding is proposed.

The present work differs from earlier works by using multi-cost routing, which is a generalization of both single-cost and multi-constrained routing, to perform efficient energy-aware routing in mesh networks. The proposed algorithms are evaluated under both a static traffic scenario without energy recharging and a dynamic traffic scenario with energy recharging. Performance bounds on the maximum achievable throughput of wireless networks with recharging are also obtained.

3. MULTI-COST ROUTING

In multi-cost routing [35], each link of the network is assigned a cost vector consisting of several cost parameters. The cost vector of a path is obtained from the cost vectors of the links that comprise it by applying, component-wise, a monotonic associative operator to each cost vector parameter. The parameters that may be included in the path cost vector are categorized by the way they are obtained from the link cost vectors, that is, by the associative operator used for each cost vector component, and by the criterion applied to them (maximization or minimization) to select the optimal path. To be more specific, we denote by $V_l = (v_{1l}, v_{2l}, \ldots, v_{kl})$, where k is the number of cost parameters, the link cost vector of link l, by $V(P) = (V_1, V_2, \ldots, V_k)$ the cost vector of the path P that consists of links $l = 1, 2, \ldots, L$, and by $f(V(P))$ the optimization function that has to be minimized in order to select the optimal path. The cost vector $V(P) = (V_1, V_2, \ldots, V_k)$ of a path P consisting of links $l = 1, 2, \ldots, L$, is then obtained from the cost vectors of the links that comprise it by applying component-wise a monotonic associative operator $\odot$ to each cost vector parameter:

$$V_m = \odot_{l=1}^{L} v_{ml}$$

The associative operator may be different for different cost vector components. For example, the mth parameter of the cost vector may be of one of the following types:

- *additive cumulative*, where

$$V_m = \sum_{l=1}^{L} v_{ml}, \quad v_{ml} \geq 0$$

and f is monotonically increasing in V_m (so our objective is to minimize V_m),

- *restrictive*, where

$$V_m = min_{l=1,\ldots,L}\{v_{ml}\}$$

and f is monotonically decreasing in V_m (so our objective is to maximize V_m), and

- *maximum representative*, where

$$V_m = max_{l=1,\ldots,L}\{v_{ml}\}$$

and f is monotonically increasing in V_m (so our objective is to minimize V_m).

Additive cumulative parameters include several important cost measures used in practice. For example, if v_{ml} is the delay on link l, then V_m represents the delay of the path, which in most practical situations has to be minimized. If $v_{ml} = 1$ for all links l, then V_m corresponds to the number of hops on the path. Since paths that use a small number of links are more economical in terms of resource utilization, it is natural to assume that the cost function f is an increasing function of V_m. If v_{ml} is the energy consumed on link l of a wireless network, then V_m represents the energy consumed for transmitting a packet on the path, which has to be minimized. Another interesting case arises when $v_{ml} \in [0, 1]$ represents the probability that link l is operational, and $V_m = \prod_{l=1}^{L} v_{ml}$ is the probability that all links on a path are operational (assuming links fail independently of each other). For the routing algorithm to favor reliable paths, the cost function f should be a decreasing function in V_m. This problem can be reduced to a problem involving cumulative additive components by defining new cost components $v'_{m1} = -\ln v_{m1}, \ldots, v'_{ml} = -\ln v_{ml}$, where $v'_{ml} \geq 0$. Then maximizing the reliability V_m of a path is equivalent to minimizing $V'_m = \sum_{l=1}^{L} v'_{ml}$.

Restrictive cost parameters appear in routing problems when capacities or transmission rates are considered. In particular, if v_{ml} is the available capacity on link l, then $V_m = \min_{l=1,\ldots,L}\{v_{ml}\}$ represents the capacity of a path, defined as the minimum of the capacities available on the links of the path. For the routing algorithm to favor less congested paths, the cost function f should be a decreasing function of V_m. Another interesting case arises when v_{ml} represents the remaining energy at the transmitting node of link l, in which case V_m represents the minimum energy available over all nodes of a path, which in most practical cases we want to maximize.

An example of a maximum representative parameter is the case where v_{ml} is the energy consumed for transmitting a packet on link l, in which case $V_m = \max_{l=1,\ldots,L}\{v_{ml}\}$ represents the most energy-expensive transmission on the path. Another example is the case where v_{ml} is the Bit Error Rate (BER) on link l, in which case $V_m = \max_{l=1,\ldots,L}\{v_{ml}\}$ represents the link with the highest BER on the path, which is often a good approximation of (or at least of the same order of magnitude with) the path BER.

It is important to note that the path that optimizes $f(V_1, V_2, \ldots, V_k)$ is generally different than the path that optimizes $\sum_{l=1}^{L} f(v_{1l}, v_{2l}, \ldots, v_{kl})$, indicating that multi-cost routing is a generalization of single-cost (shortest path) routing. Also, in contrast to single-cost routing, multi-cost routing is not always compatible with distributed routing, since for some choices of the cost function f the optimal paths do not have the inclusion property that shortest paths have; subpaths of shortest paths are also shortest paths, while this is not generally the case with optimal paths found by multicost routing for specific choices of the optimization function. These show that multi-cost routing is very different from single-cost routing both in terms of the decision it takes, its properties, and the way it is implemented.

A multi-cost routing algorithm consists of two phases. In the first phase, an enumeration of an appropriate set of candidate paths for a given source–destination pair is performed. This can be viewed as a generalization of Dijkstra's algorithm. The basic difference of this algorithm with Dijkstra's algorithm is that a set of paths between a source node and a destination node is obtained, instead of a single path. Also, a destination node for which a path has already been found may have to be considered again later. The set of candidate paths that a multi-cost routing algorithm produces at the end of the first phase, consists of the so called non-dominated paths. These are paths for which it is impossible to find other paths that are better with respect to one cost parameter (of their cost vectors) without being worse with respect to some other cost parameter. This reduces to a large extent the algorithm's computational effort, since the optimization function does not need to be applied to every possible path between a certain source–destination pair. An example of the enumeration of the non-dominated paths is given in Figure 2, where an additive cumulative parameter h and a restrictive parameter R are assumed. In the second phase, the optimal path is chosen from this set according to the optimization function $f(V)$ used.

A formal description of the multi-cost routing algorithm is presented next. The algorithm obtains for a given source S, destination E pair the optimal path. Without loss of generality, let the cost vector of each link have k cost parameters, the first s of which are additive and have to be minimized and the rest $k-s$ are restrictive and have to be maximized. We assume that each path is represented by a label that includes the cost vector associated with it and the first hop to the source using that path. The source that serves the connection is taken to be node S. We let W_i be the set of labels of the paths from node S to a node n_i, and $W \cup_{n_i \neq S} W_i$ be the set of all labels. Initially, every node has a single label corresponding to the link (if any) that connects it directly to the origin node. In each subsequent step, the algorithm marks labels (equivalently paths) from the set W as final. We let $W^f \subseteq W$ be the subset of all final labels for all the nodes, and $W_i^f \subseteq W_i$ be the set of final labels for node n_i. We also let T be the set of nodes with at least one final label. The algorithm can now be described as follows:

3.1. Phase 1—enumeration of a set of non-dominated paths

Step 0—Initialization: $W = \left\{V_{p_1}, V_{p_2}, \cdots, V_{p_N}\right\}$, $W^f = \{\}$, $T = \{\}$, where V_{p_i} is the label of the path p_i (if any) leading directly from node S to node n_i.

Step 1—Choosing the optimum label: The label of path p whose cost vector minimizes the additive component is chosen. In case of a tie, we look at the second component, which is the binary capacity availability vector, and a dominant one is chosen. If V_{p_i} is the cost vector of the chosen label and n_i is the node to which it leads, then the following updates are performed:

$$W_i^f = W_i^f \cup \{V_{p_i}\},\ W^f = W^f \cup \{V_{p_i}\},\ T = T \cup n_i. \quad (1)$$

Step 2—Obtaining the new labels: The neighbors of node n_i, which may or may not belong to the set T, are now considered and are given new labels (except for the origin node and the node specified as the previous node in the

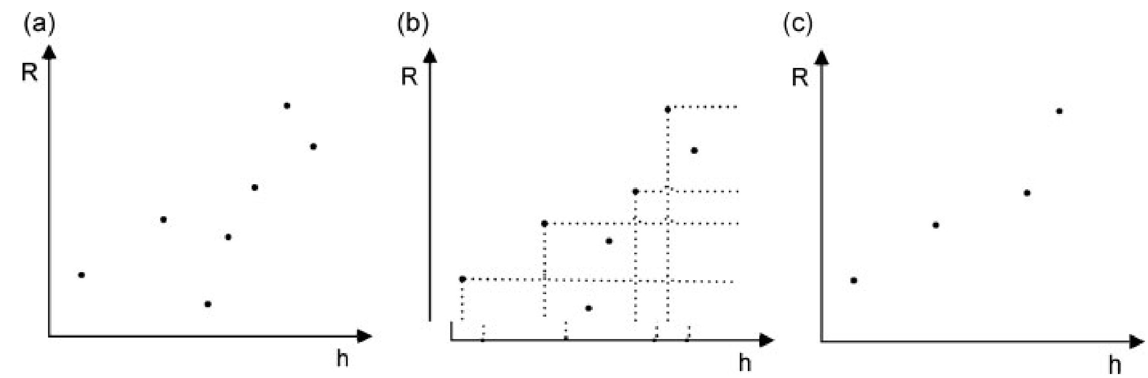

Fig. 2. Enumeration of the set of non-dominated paths, for the case of two cost parameters. Each dot represents the cost vector of a path. The parameters of this vector are an additive cumulative parameter h (representing, for example, the number of hops or the delay of the path) and a restrictive parameter R (representing, for example, the minimum residual energy on the nodes of the path or the available capacity on the path). (a) The set of all paths. (b) Obtaining the non-dominated paths. (c) The set of non-dominated paths; paths that have both larger R and smaller h than some of the other path that have been discarded.

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DOI: 10.1002/wcm

label). The new label for the path p_j leading to the neighbor n_j of node n_i by extending the path p_i through the link $l = (n_i, n_j)$ is then computed as follows. The new cost vector is updated according to $V'_{p_j} = V_{p_i} \odot V_l$, where V_l is the label of link $l = (n_i, n_j)$, and $\odot$ represents the monotonic associative operator described earlier.

Step 3—Discarding dominated paths: Each neighbor considered in step 2 compares its new label with its previous labels using the domination relation.

Let n_j be one of the neighbors of node n_i, V'_{p_j} the new label obtained from step 2 and W_j be the set of labels for this node.

The new label has to be compared with the labels $V_{p_j} \in W_j$ (both final and non-final). If any cost vector in W_j dominates V'_{p_j}, then V'_{p_j} is discarded and W_j and W does not change. If the new cost vector V'_{p_j} is not dominated by any of the vectors in W_j then V'_{p_j} is added to the set W_j and W so that $W_j = W_j \cup \{V'_{p_j}\}$ and $W = W \cup \{V'_{p_j}\}$. If the new vector dominates one of the vectors in W_j then W_j and W are updated by eliminating the dominated vectors and adding the new vector V'_{p_j}. Note that it is not possible for the new vector to dominate an existing vector and be dominated by another one at the same time.

Step 4—Termination: If after an iteration the set W^f is equal W, the algorithm is completed. Otherwise (when there are still some labels to be chosen), we go back to Step 1. The set P_{n-d} of non-dominated paths from the given source S to the given destination node E is the final set W_E^f.

3.2. Phase 2–selection of the optimal path

In the second phase, the optimal path is chosen from this set according to the optimization function $f(V)$ used. The final cost of a path P is given by a function $f(V(P))$ of its cost vector $V(P)$, and the routing algorithm selects the path with the minimum cost from the set of non-dominated paths.

In this work, we examine multi-cost routing in the context of wireless networks. The broadcast nature of the wireless medium is a major differentiating factor compared to the wired field. Additionally, the cost parameters and the optimization functions that combine them are tailored for the needs of such networks. We note here that, even in the wired networks literature, there are very few works regarding multi-cost routing (there are some works on multi-constrained routing, which is a related but different concept).

4. COST PARAMETERS AND OPTIMIZATION FUNCTIONS

The multi-cost algorithms we propose for energy aware routing in wireless mesh networks use three link cost parameters: the hop count, equal to 1 for all links, the residual energy R_i, and the transmission power T_i at the transmitting node i of a link (i, j). The number of hops h of a path is obtained by counting the links that belong to it, and is an additive cost parameter. The minimum residual energy R of a path represents the minimum residual energy left on the nodes of the path, and is a restrictive cost parameter. Finally, the transmitted power parameter T of a path is defined as the sum of the transmission powers T_i of the path's nodes and is an additive cost parameter.

The proposed optimization functions $f(h, T, R)$ are listed below. Given that we focus on energy-efficiency, we combine the aforementioned energy-related cost parameters in several ways. Each optimization corresponds to a different routing algorithm, since it produces a distinct set of routing decisions.

- *Minimum-Hop*: $f_1(h, T, R) = h$
- *SUM/MIN Energy*: $f_2(h, T, R) = \frac{\sum_{i \in P} T_i}{\min_{i \in P} R_i}$
- *SUM/MIN Energy-Hop*: $f_3(h, T, R) = h \cdot \frac{\sum_{i \in P} T_i}{\min_{i \in P} R_i}$
- *SUM/MIN Energy-Half-Hop*: $f_4(h, T, R) = \sqrt{h} \cdot \frac{\sum_{i \in P} T_i}{\min_{i \in P} R_i}$

In all cases, the algorithms first find the set of non-dominated paths with cost parameters (h, T, R), and therefore they have the same (or similar, if the parameters are not the same) Phase 1, and then use the corresponding optimization function $f(h, T, R)$ in the Phase 2, to select the optimal path. In other words the computation of the set of non-dominated paths is common to all algorithms and the selection of the optimal path is done at the end in a way that is different for each of the algorithms proposed. The function to be optimized at the last step may depend on the QoS requirements of the user. The optimization functions considered penalize paths that use a large number of hops, or consume a large amount of energy, or pass through nodes that have little energy left, differentiating, however, from each other by giving different importance to each of these factors.

The optimization functions presented, except for the first one, cannot be optimized over all paths by using a single-cost routing algorithm, which shows that multi-cost routing is a strict generalization of single-cost routing. Finally, based on Reference [27], the complexity of any algorithm (optimization function) using at least two additive parameters is exponential, except in the case where one of the two is the hop metric. Also when one additive and one restrictive or maximum representative parameter are used, then the complexity of the corresponding algorithm (optimization function) is polynomial. As a result all the proposed algorithms have polynomial complexity.

5. PERFORMANCE RESULTS UNDER THE NETWORK EVACUATION MODEL

We first evaluate the performance of the proposed energy-aware multi-cost routing algorithms under the network evacuation model. In this model, the network starts with a certain number of packets that have to be routed and a certain amount of energy per node, and the objective is to serve the packets in the smallest number of steps, or to serve as many packets as possible before the energy at the nodes is depleted. We implemented the proposed algorithms and carried out corresponding experiments using the Network Simulator [36]. The routing agent running on each node calculates the set of non-dominated paths to all destinations at periodic time intervals.

We assume that source routing is used, since, as discussed earlier, for some choices of the optimization function multi-cost routing is not amenable to distributed implementation (the inclusion property may not hold). When a data packet is generated at a node, the node applies the optimization function to the cost vectors of the corresponding non-dominated paths to select the optimal path, and the packet is sent on that path. If no route to the destination can be found, the packet is discarded.

The wireless mesh network simulated consists of 49 stationary nodes placed along a 7×7 grid. The distance between neighbouring grid points is set at 50 m. The topologies studied in the experiments are either a regular grid topology (where the transmission range of the nodes is fixed at 50 m) or a random topology (where the transmission range varies from node to node, and is uniformly distributed between 50–100 m in one set of experiments, and between 50–150 m in another set of experiments). The transmission powers used for each of the transmission ranges considered in the simulations, namely 50, 100, and 150 m, are 0.0704694, 0.281838, and 0.634135 mW, respectively. The topologies for the variable transmission range scenarios are shown in Figure 3. For the case of randomly produced network topologies each measured value represented in the graphs corresponds to the average of a set of ten experiments.

The initial energy of the nodes was taken to be either 100 or 2 J. The former case represents a scenario of essentially unlimited energy reserves ('infinite' energy), while in the latter case some nodes run out of energy during the experiments (finite energy), depending on the amount of traffic they end up serving. The number of packets per node that have to be delivered to their destinations ('evacuated' from the network) in our experiments, varies from 100 to 1000 (at steps of 100) packets per source node. All packets have equal length that is taken to be 500 bytes. Packet destinations are uniformly distributed over all remaining network nodes and the packet generation rate at each node is equal to 0.1 packets/s. The interval between non-dominated path recalculations is equal to 1 s.

In the experiments conducted we measured the average residual energy E remaining at the nodes at the end of each experiment, the variance σ^2 of the node residual energies, the time when a node runs out of energy, referred to as the node depletion time DT, the average number of hops h on the paths taken by the packets, the received-to-sent packets ratio RS and the number of collisions C between data packets.

5.1. Energy related performance measures

Figure 4 illustrates the average residual energy in the network at the end of an evacuation experiment, as a function of the number of packets evacuated per node. The Minimum-Hop algorithm results in a higher average residual energy E at the end of the evacuation experiments than the other

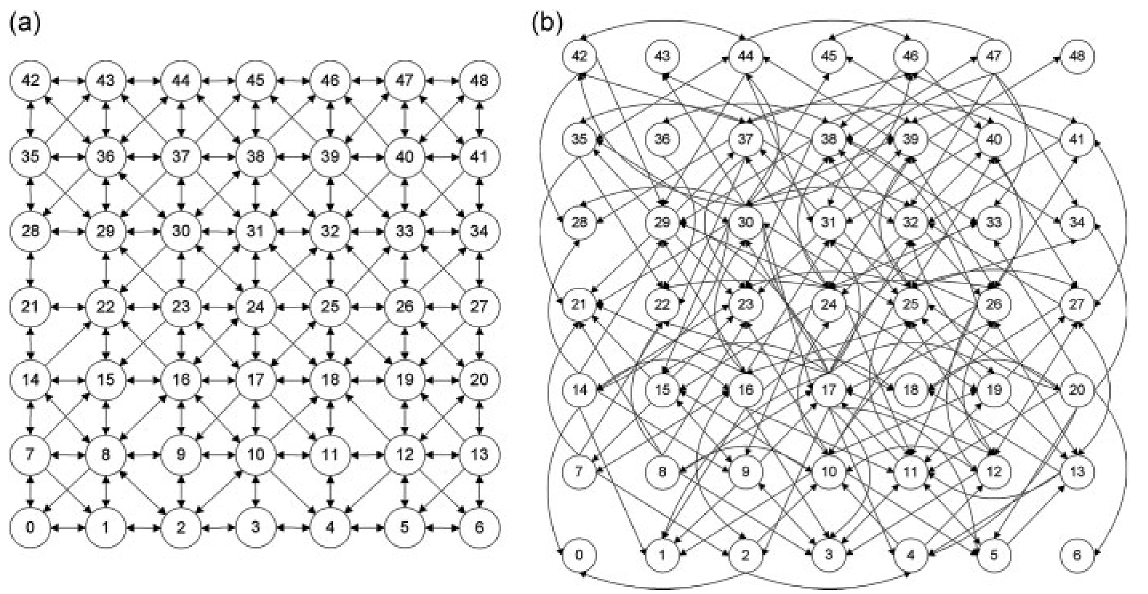

Fig. 3. (a) Network topology where the transmission range of the nodes varies between 50 and 100 m and (b) network topology where the transmission range of the nodes varies in the range 50-150 m (we omit the edges already shown in topology Figure 3a).

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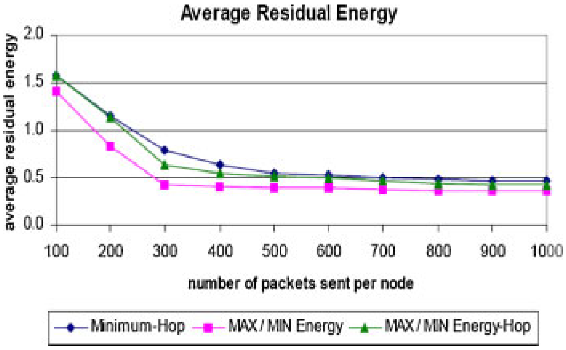

Fig. 4. Illustrates the average residual energy at the end of the evacuation experiment for the Minimum-Hop, SUM/MIN Energy, and SUM/MIN Energy-Hop algorithms. The results were obtained for the case of finite energy and the topology of Figure 3a.

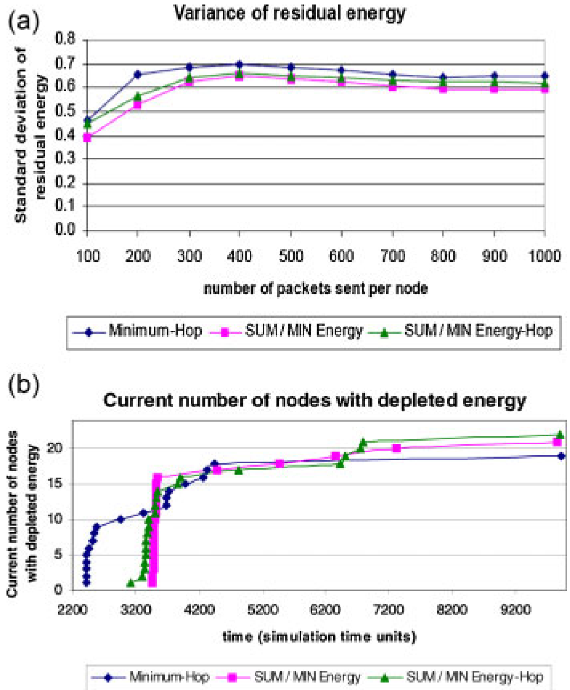

Fig. 5. Illustrates (a) the variance of the residual energy and (b) the current number of nodes with depleted energy at the end of the evacuation experiment for the Minimum-Hop, SUM/MIN Energy, and SUM/MIN Energy-Hop algorithms. The results were obtained for the case of finite energy and the topology of Figure 3a.

routing algorithms examined. However, the Minimum-Hop algorithm also results in a less uniform energy consumption in the network and in smaller energy depletion times DT than the other algorithms, indicated by Figure 5a and 5b, respectively. As a result the Minimum-Hop algorithm also achieves lower throughput and higher dropping ratio. Note in Figure 4 that when more than 400 packets are generated per source node, then the average residual energy stops decreasing for all algorithms examined. This happens because many nodes run out of energy and consequently the network becomes disconnected and no more packets are served.

The Minimum-Hop algorithm uses the same path for the entire duration of a session, or until the energy of a node on the path is depleted. As a result, a relatively small subset of nodes has more active participation, in the transmission of packets, than other nodes. The SUM/MIN Energy and SUM/MIN Energy-Hop algorithms, on the other hand, are based on parameters (namely R_i) that change over time, and the path selected may not remain the same for all the packets of a session. In this way the traffic forwarding and the resulting energy consumption are spread more uniformly, over a larger number of nodes, leading to smaller average residual energy E and smaller variance σ^2 of the residual energy than the Minimum-Hop algorithm. Regarding the time the energy of the nodes is depleted, the SUM/MIN Energy-Hop algorithm exhibits the best performance in all the experiments, while the Minimum-Hop algorithm seems to result in the worst DT. Note that with the SUM/MIN Energy and SUM/MIN Energy-Hop algorithms, when nodes start running out of energy, this happens almost simultaneously for all nodes. This is because these algorithms spread the energy consumption uniformly in the network, so that when one node is at the point of first running out of energy, most other nodes are at the same energy-critical situation.

In most of the experiments conducted, we found that the performance of the SUM/MIN Energy-Hop algorithm was between that of the Minimum-Hop algorithm and that of the SUM/MIN Energy algorithm, and, actually, in most cases it was closer to that of the Minimum-Hop algorithm. The SUM/MIN Energy-Half-Hop algorithm was found to behave very similarly to the SUM/MIN Energy algorithm in all cases considered. It seems that the 0.5 exponent on the number of hops in the former algorithms effectively eliminates the impact of the hop term on the cost function. This is the reason we chose not to present in great detail the results on the SUM/MIN Energy-Half-Hop algorithm.

5.2. Network related performance measures

Figure 6 shows the received-to-sent packets ratio RS for various algorithms examined. When the initial energy of the nodes is infinite, all the packets are delivered to their destinations, but when the initial energy is finite, the fraction of packets delivered to their destinations decreases after a certain number of packets have been inserted in the network. The reason is that nodes run out of energy, limiting the ability of the network to route packets. We observed that the SUM/MIN Energy-Hop SUM/MIN Energy algorithms achieve the best RS ratio in almost all the experiments, since with these algorithms the network nodes remain alive for longer periods of time.

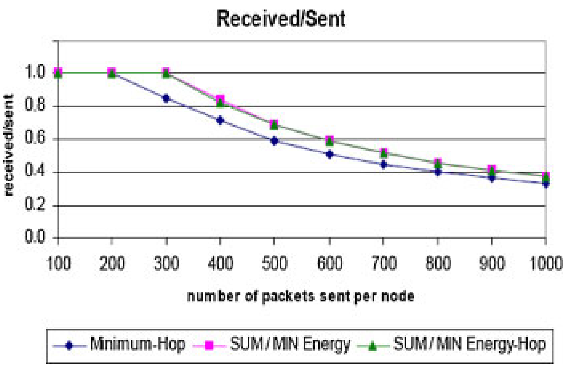

Fig. 6. Illustrates the received-to-sent packets ratio for the Minimum-Hop, SUM/MIN Energy, and SUM/MIN Energy-Hop algorithms. The results were obtained for the case of finite energy and the topology of Figure 3a.

Figure 7 shows the average number of hops of the path. When the nodes energy is infinite or the number of packets exchanged is small, the SUM/MIN Energy algorithms selects paths that are longer on average than the Minimum-Hop paths. However, when the nodes have finite energy, there are cases where SUM/MIN Energy algorithm achieves similar average number of hops to that of the Minimum-Hop paths. This is because some of the nodes run out of energy and the Minimum-Hop algorithm, eventually, has to use longer paths. The SUM/MIN Energy-Hop algorithms are dominated by the hop parameter and give results that are similar to those of the Minimum-Hop.

5.3. The overhead of information exchange

The operation of the multi-cost algorithm is based on the knowledge of the cost parameters by the nodes, some of which (e.g., the node residual energy) are time-varying.

In wireless mesh networks or in *ad hoc* networks, the cost parameter updates can be achieved by a periodical beacon-like protocol, according to which each node sends its local information to its direct neighbors. Eventually this information will reach all the nodes in the network. An alternative approach would be to include the updates on cost parameters used, in the control and data packets (piggybacking) exchanged among the nodes, and used for making routing decisions. This is particularly true for mobile *ad hoc* networks, where the network topology and residue energy of individual nodes are all subject to change; therefore, residual energy information can be piggybacked in control packets that are exchanges anyway for updating topology and hop count information. Wireless mesh networks, however, usually have minimum-mobility mesh backbones, and hop counts are relatively static information. Therefore, exchanging residual energy information will require additional control packets. In any case, there will be a difference between the values of the parameters stored at each node and the actual values of the parameters that is expected to grow with the network diameter. When various cost parameters participate in the selection of the optimal paths, a subset of which are time-varying, it can be argued that this information staleness is not decisive for the efficiency of multi-cost routing. This is indeed supported by our simulation experiments to be described shortly.

In our simulations, we implemented the information exchange process through the periodic update of the values of the cost parameters stored at the network nodes. In order to investigate the effect of the staleness of the parameter values, we studied the algorithm's performance with respect to the duration of the information update interval. The algorithms examined in this set of simulations were the SUM/MIN Energy and the SUM/MIN Energy-Hop algorithms.

The experiments conducted, depicted in Figure 8, verify that the performance of the energy-aware algorithms degrades as the update interval increases. Interestingly, there is a certain threshold in the update interval under which the performance of the energy-aware routing algorithms is not seriously degraded. In the results of Figure 8 this threshold is observed to be between 5 and 10 s.

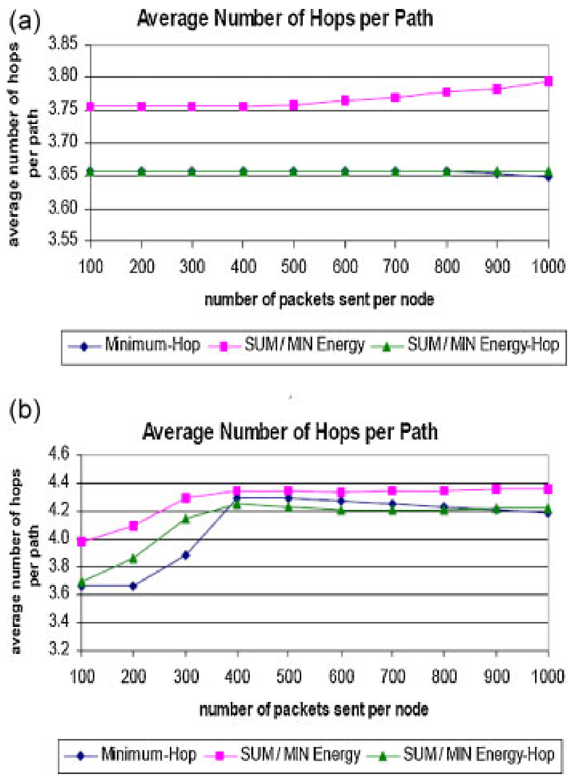

Fig. 7. Illustrates the average number of hops of the paths constructed by the Minimum-Hop, SUM/MIN Energy, and SUM/MIN Energy-Hop algorithms. The results were obtained for the case of (a) infinite (very large) and (b) finite energy and the topology of Figure 3a.

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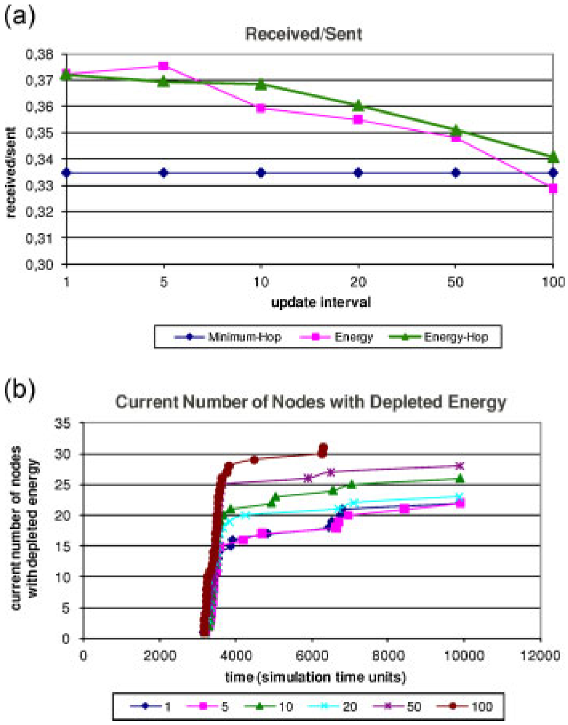

Fig. 8. Illustrates (a) the received to sent packets ratio for the SUM/MIN Energy and SUM/MIN Energy-Hop algorithms and (b) the current number of nodes with depleted energy for the SUM/MIN algorithm. The results were obtained for the case of finite energy and the topology of Figure 3a, assuming each node sends 1000 packets to randomly chosen destinations.

However, in comparison to the Minimum-Hop algorithm, multi-cost routing performs considerably better even for update interval of 100 s. This observation illustrates that multi-cost routing withstands a certain amount of staleness in the information regarding the cost parameters. Therefore, multi-cost routing can still produce significant improvement in network performance even when a relatively lighweight information collection mechanism is used, such as one based on data and control packets piggybacking, which cannot always guarantee up-to-date information to the network nodes. This observation justifies that multi-cost routing is a scalable approach for wireless mesh networks. Furthermore, the same conclusion was drawn in Reference [1], where we studied the application of multi-cost routing in mobile *ad hoc* networks by incorporating it in the standard DSR algorithm. In that case the information update was implemented by piggybacking the information of the cost parameters in the data and control packets exchanged by the nodes.

6. CAPACITY AND ENERGY LIMITATIONS

Starting with this section, we turn our attention to the dynamic one-to-one communication model. In the dynamic one-to-one communication problem (see Figure 1) packets having uniformly distributed destinations are generated at each network node according to a random process, and energy is also added at each node at a given recharging rate, over an infinite time horizon. In our study, we first present upper bounds on the maximum achievable throughput of two-dimensional networks under capacity and energy limitations. In the next section we present simulation results on the performance of multi-cost routing under the dynamic one-to-one communication model.

The traffic load that can be inserted in a wireless mesh network is restricted by capacity and interference limitations, and by the energy recharging rate at the nodes. Several works have examined the effect link capacities and interference have on the maximum achievable throughput [37,38], but little work has been done on the limitations on the maximum throughput posed by energy considerations.

We assume that packets are generated at each node of an N-node network with probability p during each time period (slot), and each packet requires an average of $h(p)$ transmissions to arrive at its destination. All transmissions have a transmission range R and require energy E. In a network of area A, the number of transmissions that can take place simultaneously is upper bounded by $\frac{A}{kR^2}$, where k is a constant between π and 4π that depends on the MAC protocol used and the relative location of the nodes, as shown in Figure 9. The mean number of transmissions per slot is given by the product $N \cdot p \cdot a(p) \cdot h(p)$, where $h(p)$ is the average number of hops of the paths, and $a(p)$ is the ratio of the total number of packet transmissions over the number of successful transmissions required to get the packets to their destinations over the paths chosen. For the network to be stable the following inequality must hold

$$N \cdot p \cdot a(p) \cdot h(p) \leq \frac{A}{kR^2}.$$

The number of hops of the paths $h(p)$ is roughly inversely proportional to the transmission range R of the nodes, and we have $h(p) \geq L/R$, where L is the average physical source–destination distance (with the inequality being closer to equality for dense networks and shortest distance routing). Assuming we are in the stable region and there is no buffer limitation, no packets are lost, and we have $a(p) \geq 1$. Consequently, a limit on the packet generation rate p posed by the capacity/interference constraints is given by

$$p \leq \frac{A}{kRNL} = \frac{1}{k\rho L} \cdot \frac{1}{R}, \qquad (2)$$

where $\rho = N/A$ is the area node density.

For a wireless mesh network with energy rechargeable nodes to be stable, the mean energy expended at each time slot must not exceed the energy inserted in the network in the same period. The average energy expended during each slot is equal to $N \cdot p \cdot a(p) \cdot h(p) \cdot E$, while the average energy inserted in the network during a slot is equal to $N \cdot X$, where X is the energy recharging rate at each node per slot. Consequently, a necessary condition for the network to be stable is

$$N \cdot p \cdot a(p) \cdot h(p) \cdot E \leq N \cdot X.$$

Assuming we are in the stable region and there is no buffer limitation, no packets are lost, and we have $a(p) \geq 1$. The energy expended E for a packet transmission can be expressed as $k'R^{\alpha}$, for some constant k' (which depends on the channel, the sensitivity of the receiver, and the desired BER), where α is between 2 and 4 depending on the power-loss model. Working as before (e.g., $h(p) \geq L/R$) we find that a necessary condition for stability due to the energy constraint is

$$p \leq \frac{X}{k'L} \cdot \frac{1}{R^{\alpha-1}}. \tag{3}$$

Inequalities 2 and 3 show that the dependence of the energy limitation on the network nodes' transmission range R is stronger (since $\alpha > 2$) than the dependence of the network capacity/interference limitation on R. The stability region shrinks as the transmission range R increases, showing that a small transmission range is beneficial both for capacity/interference-constrained and energy-constrained wireless mesh networks. That is, the amount of traffic that can be served by the network increases when we decrease the transmission range of the nodes, both due to increasing network capacity (better reuse factor) and due to lower spending of the energy reserves. Since in most wireless environments $\alpha > 2$ (α is close to 4 for urban environments), we can conclude (at least for dense networks) that for R sufficiently small the network throughput is mainly constrained by capacity/interference limitations, while for R sufficiently large it is constrained by energy limitations.

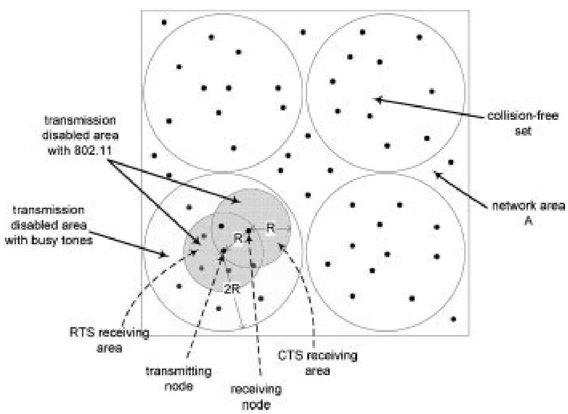

Fig. 9. In the IEEE 802.11 protocol, widely used in wireless mesh networks, a node wishing to transmit a packet at distance R, first uses the RTS/CTS mechanism to reserve a transmission floor of area between πR^2 and $4\pi R^2/3$ around it (depending on the distance of the transmitter and the intended receiver), and the nodes located in this area (depicted in grey) cannot transmit. Wireless mesh networks that do not use 802.11 often use busy tones [3] to avoid the hidden terminal problem. In that case all nodes hearing a packet transmission start sending a busy tone, and all nodes who hear the busy tone are prevented from transmitting. If the node density is high, all nodes at a distance of about $2R$ from a transmitting node (in a total area of $4\pi R^2$) are prevented from transmitting. Therefore, the number of nodes disallowed when a given transmission takes place is similar (within a constant factor) when a busy tone mechanism or an RTS/CTS mechanism is used, and is proportional to R^2.

Equations (2) and (3) show that the capacity/interference limitation and the energy limitation depend in similar ways on the average physical distance L in the network, with the achievable throughput per node falling as L increases. Another conclusion drawn from the above discussion is that even though the capacity/interference limitation decreases as the area node density ρ increases, the energy limitation is independent of ρ. In summary, we expect networks that are sparse or that have a small recharging rate X, or use a large transmission radius R to be mainly energy-limited as opposed to capacity/interference limited.

7. PERFORMANCE RESULTS UNDER THE DYNAMIC ONE-TO-ONE COMMUNICATION MODEL

In this section we compare the performance of the SUM/MIN Energy algorithm, presented in Section 4, to that of the Minimum-Hop algorithm in the context of the dynamic one-to-one communication model. Under this model, packets are generated at each network node according to a random process, and energy is also added at each node at a given recharging rate, over an infinite time horizon. All packets are assumed to have equal length, and require one slot in order to be transmitted over a link. Time is slotted, and a new packet is generated at each node with probability p during a slot. In our experiments, the duration of the slot is 0.08 s while the packet transmission time 0.016576 s, for the 2000 bytes sized packets we use in our experiments. We chose this slot time in order for the RTS/CTS handshake mechanism to have been completed by the time the next packet is generated. Packet destinations are uniformly distributed over all nodes.

In addition to the usual capacity and interference constraints, the network is also assumed to be energy-constrained. More specifically, we assume that energy is generated at each node at a recharging rate of X units of energy per slot. Initially the network is without energy. Each packet transmission consumes an equal amount of energy E. Furthermore, we define a threshold on the residual energy of a node, and when the energy at a node falls below this threshold, the node stops forwarding packets and starts storing them in its queue. The same happens when the receiver's residual energy is below this threshold. Each node periodically checks its energy reserves and those of its neighbours, and if they both exceed the threshold the node starts forwarding its queued packets.

We are interested in the steady-state performance of the proposed schemes for varying recharging rates and packet generation probabilities. The network is assumed to have reached the steady state when the variance in the packet delivery delay is below some threshold. The network topol-

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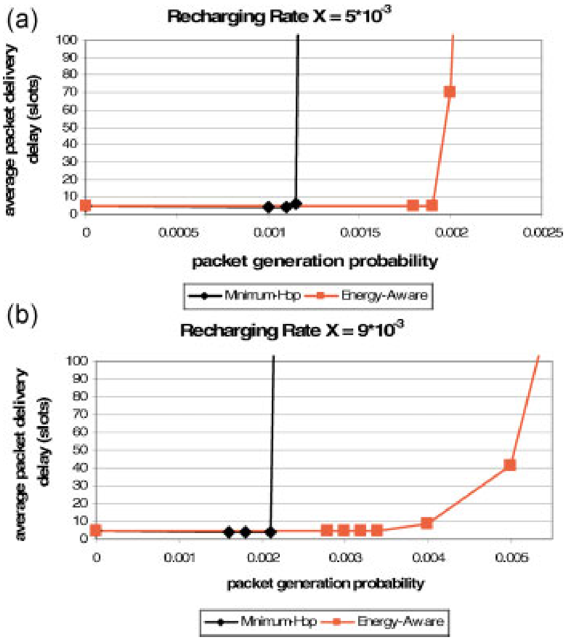

Fig. 10. Illustrates the packet delay (in slots) as a function of the packet generation rate p for the Minimum-Hop and the SUM/MIN Energy (Energy-Aware) algorithms, for energy recharging rates of (a) $X = 5 \cdot 10^{-3}$ Joules per slot and (b) $X = 9 \cdot 10^{-3}$ Joules per slot.

ogy in our experiments is that of Figure 3a where the transmission range of the network nodes is uniformly distributed between 50 and 100 m. The performance metrics of interest are the largest packet generation probability $p_{\max}$ for which the network remains stable (maximum throughput) and the average packet delivery delay for a given packet generation probability $p < p_{\max}$. By stability we mean that the incoming traffic can be served appropriately, with small average packet delay and high packet delivery ratio. When either of these conditions is broken, the network is assumed to enter the unstable region and there is no point in further studying it. Each measured value, represented in the graphs, corresponds to the average of a set of 10 experiments.

Figure 10 shows the average packet delay as a function of the packet generation rate p, for recharging rates of $X = 5 \cdot 10^{-3}$ and $X = 9 \cdot 10^{-3}$ Joules per slot,[‡] for both the Minimum-Hop and the SUM/MIN Energy routing algorithms. The SUM/MIN Energy algorithm outperforms the Minimum-Hop algorithm, by enabling the network to remain stable for heavier traffic loads. For the topology considered, the traffic generation probabilities p that the SUM/MIN Energy algorithm is able to handle, with adequately small packet delivery delay, are nearly twice those of the Minimum-Hop algorithm, for both recharging rates considered. The transition of the network to the unstable region, as indicated by the rise in the average packet delay in Figure 10, is very steep for the Minimum-Hop algorithm for both recharging rates $X = 5 \times 10^{-3}$ and $X = 9 \times 10^{-3}$ Joules per slot: from values of the delay around 4 or 5 slots in the stable region, there is an almost instant increase to large (practically infinite) values above 100 slots. This is because when the Minimum-Hop algorithm (which is not energy-efficient) is used, the network for both values of the recharging rate X is energy constrained. When the energy at some nodes gets depleted, the energy of many other nodes also starts getting depleted soon afterwards, and the rise in the delay is very abrupt. In this state, the delivery of the incoming packets becomes difficult (large delays) or impossible (dropping of packets) due to the weakened connectivity of the network. When the SUM/MIN Energy algorithm is used and for the low recharging rate $X = 5 \times 10^{-3}$ Joules per slot the network is again energy-constrained, but because it uses energy more efficiently, the rise in the delay is less abrupt than with the Minimum-Hop algorithm. When the SUM/MIN Energy algorithm is used and the recharging rate is relatively high, $X = 9 \times 10^{-3}$ Joules per slot, the network is mainly capacity-constrained and the rise in the delay is rather smooth.

Figure 11 shows the number of packets received with respect to the number of packets sent, for recharging rates $X = 9 \times 10^{-3}$ and $X = 15 \times 10^{-3}$ Joules per slot. It can be observed that the SUM/MIN Energy algorithm achieves a higher throughput than the Minimum-Hop algorithm, since the degradation of the received-to-sent packets ratio begins later than with the Minimum-Hop algorithm. For both algorithms, the number of packets delivered to their destinations grows linearly, initially, with the number of packets that enter the network, since for light traffic few packets are dropped. For packet generation probabilities greater than $p_{\max}$, however, there is a steep decline in the packet delivery ratio. The number of packets successfully delivered to their destinations not only stops increasing as the number of incoming packets grows, but it even declines after the network enters the unstable region.

Figure 12 shows the maximum throughput (maximum packet generation probability) $p_{\max}$ for which the network remains stable as a function of the recharging rate X at the network nodes, for both the Minimum-Hop and the SUM/MIN Energy routing algorithm. The maximum throughput $p_{\max}$ achieved by the network is taken to be the highest packet generation probability for which the network manages to serve the incoming traffic appropriately, meaning with small average packet delivery delay and high packet delivery ratio. The thresholds set for these two metrics used for detecting experimentally when the network enters the unstable region (above 100 slots for the average packet delivery delay and under 80% for the delivery ratio) are not important qualitatively for the results obtained, since we found that a different setting of the thresholds only causes a small shift in the values presented without altering any of the conclusions drawn.

Figure 12 shows that the SUM/MIN Energy algorithm outperforms the Minimum-Hop algorithm, achieving significantly larger $p_{\max}$ for all recharging rates considered.

[‡] To be more specific, energy equal to 0.005 and 0.009 J was offered every 10 s in the experiments.

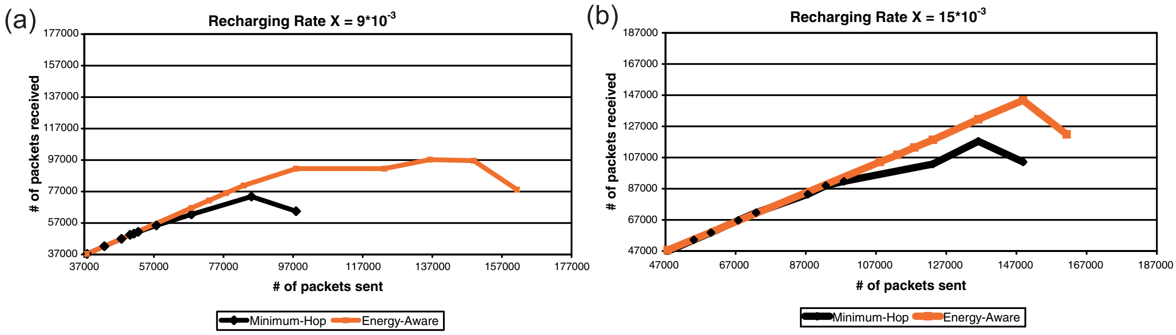

Fig. 11. The number of the packets received *versus* the number of packets sent for the Minimum-Hop and the SUM/MIN Energy (Energy-Aware) algorithms, for energy recharging rates of (a) $X = 9 \cdot 10^{-3}$ Joules per slot and (b) $X = 15 \cdot 10^{-3}$ Joules per slot.

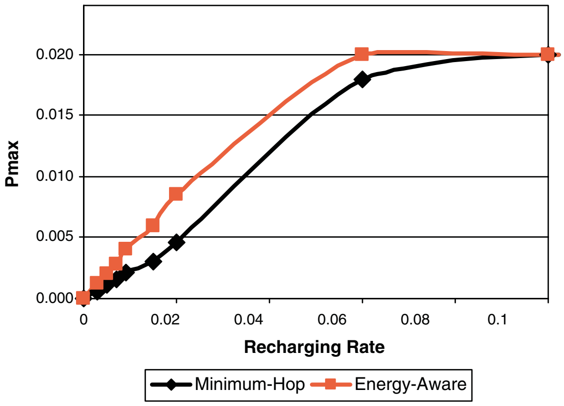

Fig. 12. The maximum throughput (maximum packet generation probability) p_{max} for which the network remains stable as a function of the recharging rate X (Joules per 10 s) at the network nodes, for the Minimum-Hop and the SUM/MIN Energy (Energy-Aware) algorithms.

The maximum throughput p_{max} seems to depend on the recharging rate almost linearly until the very end, for both routing algorithms. This linear increase verifies that the network in this region of recharging rates is energy-constrained.

When the recharging rate increases beyond some point, the network starts getting constrained by capacity/interference limitations, and the rate at which p_{max} grows with respect to the recharging rate is slowed down, until it reaches a plateau indicating that the capacity/interference limitation has been reached. The performance difference between the SUM/MIN Energy algorithm and the Minimum-Hop algorithm is larger for low energy recharging rates at the nodes, and the difference is gradually reduced as the limitation posed by the network capacity is approached. The maximum throughput p_{max} achieved by the SUM/MIN Energy algorithm is nearly twice that of the Minimum-Hop algorithm. This is because the further away the network is from the capacity-constrained region, the more important becomes the efficiency in the use of the energy resources. In summary, when energy is the factor defining the ability of the network to serve incoming traffic, the SUM/MIN Energy algorithm performs better. However, as energy becomes abundant and capacity becomes the main limitation on network performance, the performance gap between the SUM/MIN Energy and the Minimum-Hop algorithm is narrowed.

8. CONCLUSIONS

We proposed and evaluated the performance of several multi-cost energy-aware routing algorithms for wireless mesh networks. Multi-cost routing is a generalization of both single-cost and multi-constrained routing, and is significantly more powerful than these approaches. In the experiments conducted under the network evacuation model we found that the multi-cost energy-aware routing algorithms distribute the traffic more uniformly across the network, prolonging its lifetime and improving its performance. More specifically, the Energy-Hop algorithms were found to have better performance than both the Energy and the Minimum-Hop algorithms, under the energy and network related performance measures used. We then turned our attention to the dynamic one-to-one communication model, where mesh nodes are able of recharging their energy, and examined the impact the capacity and energy constraints have on network performance for two-dimensional networks. We also evaluated the performance of multi-cost energy-aware routing algorithms under this model and showed that they achieve a very satisfactory average delay and maximum throughput (the throughput is twice that of minimum-hop routing when the network is energy-constrained).

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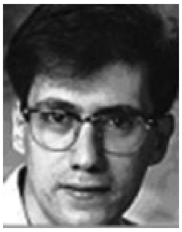

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Wirel. Commun. Mob. Comput. 2013; **13**:424–438 © 2011 John Wiley & Sons, Ltd.
DOI: 10.1002/wcm