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Energy aware efficient geographic routing in lossy wireless sensor networks with environmental energy supply

Kai Zeng · Kui Ren · Wenjing Lou · Patrick J. Moran

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Abstract Wireless sensor networks are characterized by multihop wireless lossy links and resource constrained nodes. Energy efficiency is a major concern in such networks. In this paper, we study Geographic Routing with Environmental Energy Supply (GREES) and propose two protocols, GREES-L and GREES-M, which combine geographic routing and energy efficient routing techniques and take into account the realistic lossy wireless channel condition and the renewal capability of environmental energy supply when making routing decisions. Simulation results show that GREESs are more energy efficient than the corresponding residual energy based protocols and geographic routing protocols without energy awareness. GREESs can maintain higher mean residual energy on nodes, and achieve better load balancing in terms of having smaller standard deviation of residual energy on nodes. Both GREES-L and GREES-M exhibit graceful degradation on end-to-end delay, but do not compromise the end-to-end throughput performance.

Keywords Wireless sensor networks · Geographic routing · Energy efficiency · Environmental energy supply

K. Zeng (✉) · K. Ren · W. Lou
Department of ECE, Worcester Polytechnic Institute, MA 01609
e-mail: kzeng@wpi.edu

K. Ren
e-mail: kren@wpi.edu

W. Lou
e-mail: wjlou@wpi.edu

P. J. Moran
AirSprite Technologies, Inc., Northborough, MA 01532
e-mail: pmoran@airsprite.com

1 Introduction

Wireless sensor networks (WSNs) are characterized by multihop lossy wireless links and severely resource constrained nodes. Among the resource constraints, energy is probably the most crucial one since sensor nodes are typically battery powered and the lifetime of the battery imposes a limitation on the operation hours of the sensor network. Unlike the microprocessor industry or the communication hardware industry, where computation capability or the line rate has been continuously improved (regularly doubled every 18 months), battery technology has been relatively unchanged for many years. Energy efficiency has been a critical concern in wireless sensor network protocol design. Researchers are investigating energy conservation at every layer in the traditional protocol stack, from the physical layer up to the network layer and application layer.

Among the energy consumption factors, communication has been identified as the major source of energy consumption and costs significantly more than computation in WSNs [1]. Energy aware routing and geographic routing are two major approaches to energy efficient communications in wireless ad hoc and sensor networks.

In former energy aware routing protocols [2–5], sensors/nodes are assumed to be powered by batteries with limited/fixed capacity and then routing decisions are made based on the energy consumption by sending/receiving packets on the wireless links and/or residual energy on each node. The objective of those protocols is either minimizing the energy consumption or maximizing the network lifetime. A new observation related to energy aware routing is the availability of the so-called energy scavengers which are devices able to harvest small amount of energy from ambient sources such as light, heat or vibration [6–8]. Solar-aware routing protocols are proposed in [9, 10] that preferably route packets via solar powered nodes. The optimal paths are calculated based on each node having global knowledge of the whole network, which is usually inapplicable in WSNs. Lin et al. [11] addressed the problem of power-aware routing with distributed energy replenishment for multihop wireless networks. The distributed algorithm proposed in [11] needs to flood the whole network to get the optimal path. More comprehensive study is necessary to design efficient localized algorithm to achieve energy efficiency with environmental energy supply.

In geographic routing [12–19], each node makes routing decision locally based on its own, its neighbors' and the destination's location information. Geographic routing technique is particularly applicable in wireless sensor networks because almost all sensing and monitoring applications of sensor networks require sensors to be aware of their physical locations. The properties such as good scalability, statelessness, and low maintenance overhead make geographic routing an efficient technique especially in large-scale WSNs. The focus of these geographic routing works was performance gain therefore none of them took into account the energy constraint on nodes. While some geographic routing protocol accounts for nodes' residual energy information such as GEAR (Geographic and Energy Aware Routing) [20], which uses energy aware and geography-based neighbor selection heuristics to route a packet towards the target region, it does not take into account the realistic wireless channel conditions. It is shown in [18] that the factor of unreliable wireless links must be explicitly taken into account when designing geographic routing protocols.

It's necessary to design new local cost metrics to achieve efficient geographic routing with environmental energy supply. In this paper, we take a cross-layer design approach and carry out a more comprehensive study on energy efficiency issue. We propose two Geographic Routing with Environmental Energy Supply (GREES) protocols, GREES-L and GREES-M, which make routing decision locally by jointly taking into account multiple factors—the realistic wireless channel condition, packet advancement to the destination, the residual battery energy level of the node, and the environmental energy supply. Simulation results show that our protocols are more energy efficient than the corresponding residual energy based protocols and geographic routing protocols without considering the property of the energy renewal. In particular, given the same energy and traffic models, GREESs maintain higher mean residual energy on nodes and achieve better load balancing in terms of having a smaller standard deviation of residual energy among nodes. Both GREES-L and GREES-M exhibit graceful degradation on end-to-end delay, but do not compromise the end-to-end throughput performance.

The rest of the paper is organized as follows. The related work is introduced in Section 2. We explain GREES-L and GREES-M in detail in Section 3, and present and analyze our simulation results in Section 4. Section 5 presents our conclusions.

2 Related work

Our work is inspired and related to prior works on energy-aware routing and geographic routing, and recent works on feasibility of using environmental energy resources in wireless sensor networks.

2.1 Energy aware ad-hoc routing

Energy-aware routing has received significant attention over the past few years [2–5]. Woo et al. [2] proposed five energy aware metrics such as *maximizing time to partition* and *minimizing maximum node cost*. These are important metrics for energy efficient routing, however, it is difficult to directly implement them in a local algorithm when even the global version of the same problem is NP-complete. Chang et al. [3] proposed a class of flow augmentation algorithms and a flow redirection algorithm which balance the energy consumption rates among the nodes in proportion to the energy reserves. The limitation of this approach is that it requires the prior knowledge of the information generation rates at the origin nodes. Li et al. [4] proposed an "online" power-aware routing and a zone based routing algorithms which maximize the network lifetime without knowing the message generation rate. Following [4], another "online" routing algorithm was proposed in [5] aiming to maximize the total number of successfully delivered messages.

All of these works were based on the assumption that nodes have limited/fixed energy supply and did not take into account the nodes' capabilities of extracting energy from the environment, which will be studied in this paper.

2.2 Geographic ad-hoc routing

The appeal of geographic routing protocol lies in the fact that it is scalable and the process of making routing decision is localized. The node holding the packets only needs to be aware of the location of itself, its one hop neighbors, and the destination. For traditional geographic routing schemes, packets are routed/forwarded locally and greedily to the one-hop neighbor that provides most positive advancement to the destination. In greedy mode, Cartesian routing [12] chooses the neighbor closest to the destination as the next hop while MFR (Most Forward within Radius) [13] prefers the neighbor with the shortest projected distance (on the straight line joining the current node and the destination) to the destination.

In recent experimental studies on wireless ad-hoc and sensor networks, Couto et al. [21], Zhao and Govindan [22] have shown that wireless links can be highly unreliable and that this must be explicitly taken into account when considering higher-layer protocols. Zuniga and Krishnamachari [23] showed the existence of a large "transitional region" where link quality has high variance, including both good and highly unreliable links. The existence of such links exposes a key weakness in greedy forwarding schemes that the neighbors closest to the destination (also likely to be farthest from the forwarding node) may have poor links with the forwarding node. The weak links would result in a high packet dropping rate and drastic reduction of delivery ratio or increased energy wastage if retransmissions are employed. More recent works on geographic routing are aware of this realistic lossy channel situation. Seada et al. [18] articulated the distance–hop energy trade-off for geographic routing. They concluded that the expected packet advancement, *PRR* (*Packet Reception Rate*) × *Advancement*, is an optimal metric for making localized geographic routing decisions in lossy wireless networks with ARQ (Automatic Repeat reQuest) mechanisms. Zorzi and Armaroli also independently proposed the same link metric [24]. Lee et al. [19] presented a more general framework called normalized advance (NADV) to normalize various types of link cost. The focus of the above works was performance gain therefore none of them took into account the energy constraint on nodes. Although GEAR (Geographic and Energy Aware Routing) [20] accounts for nodes' residual energy information, it does not take into account the realistic wireless channel conditions.

2.3 Routing in environmentally powered sensor networks

There is significant interest in energy harvesting for wireless sensor networks in order to improve its sustainable lifetime and performance [25]. Several technologies to extract energy from the environment have been demonstrated including solar light, heat or vibrational sources [6–8].

Environmental energy is distinct from battery status in two ways. First it is a continued supply which if appropriately used can allow the system to last forever, unlike the battery which is a limited resource. Second, there is an uncertainty associated with its availability and measurement, compared to the energy stored in the battery. Thus, methods based on residual energy in batteries are not always applicable to environmental energy aware decisions [26].

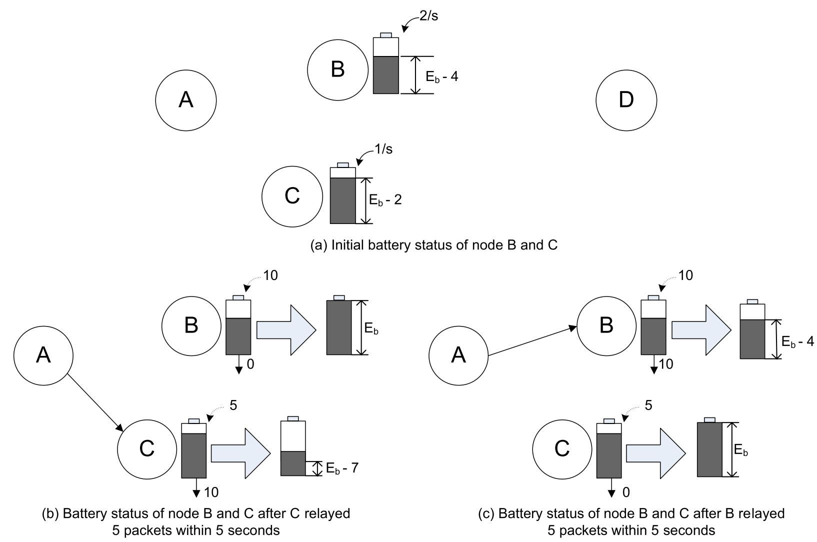
The works taking environmental energy into account for routing are [9, 10, 27, 28]. A distributed framework for the sensor network to adaptively learn its energy environment was presented in [9]. An example study of routing in [9] showed that the proposed framework is able to utilize the extra knowledge about the environment to increase system lifetime. Voigt et al. [10] designed two solar-aware routing protocols that preferably route packets via solar powered nodes and showed that the routing protocols provide significant energy savings. The optimal paths calculated in [9, 10] is based on each node having global knowledge of the whole network, which is usually inapplicable in WSNs. Although Lin et al. proposed a distributed algorithm that considers energy replenishment, it still [11] needs to flood the whole network to get the optimal path. An energy-aware geographic blacklisting routing was proposed in [28]. More comprehensive study is necessary to design efficient localized algorithm to achieve energy efficiency with environmental energy supply.

3 Geographic routing with environmental energy supply (GREES)

Our objective is to design routing protocols that efficiently direct the packets along low cost links and at the same time balance the residual energy on nodes with environmental energy supply. Although the expected advancement is a good link energy cost metric, we can not simply forward the packet to the neighbor achieving the largest expected advancement, as in this condition some nodes will be overused and die out fast then result in network disconnection. We also can not simply forward the packet to the nodes that have the highest residual energy, because the residual energy status may not represent the energy availability on nodes in some situation. The example shown in Fig. 1 illustrates this situation.

In Fig. 1(a), node A has two neighbors B and C, and A has five packets to send to a remote destination D with one packet per second. The energy consumption per packet delivery on link AB and AC are the same. Assume that B and C have the same battery capacity of E_b units, and $E_b - 4$ and $E_b - 2$ units of residual energy respectively; their energy harvesting rates are 2 and 1 units per second respectively; they consume the same energy, say 2 units, to relay (receive and forward) a packet to their next hop. For energy aware routing that only considers the residual energy information on nodes, A will send the packets to C because C has more residual energy. As shown in Fig. 1(b), after relaying the five packets, C has residual energy of $E_b - 7$ units since it consumes 10 units for relaying the packets meanwhile harvesting 5 units, and B is fully recharged since it harvests 4 units of energy. Although B can harvest 10 units of energy in five seconds, the residual energy on it can not exceed the battery capacity, E_b. For environmental energy aware protocol, assume we define the energy availability as the sum of the battery residual energy and the harvesting energy during the routing period (5 seconds), B has higher energy availability than C, then B will be selected as the next hop of A. As shown in Fig. 1(c), after relaying the five packets, B has residual energy of $E_b - 4$ units since it consumes 10 units for relaying packets meanwhile harvesting the same amount of energy, and C was fully recharged since it harvests 2 units of

Fig. 1 Comparision of battery status of intermediate nodes between residual energy based protocol and environmental energy aware protocol



energy. In this example, using environmental energy aware routing results in more residual energy remained on nodes on average and smaller variance of the residual energy which indicates better load balancing.

3.1 System model

We first describe the system model, the observations and the assumptions, on which our routing protocol design is based.

We assume that each network node is aware of its own and its one-hop neighbors' positions and the source of a message knows the position of the destination. This assumption is reasonable in a wireless sensor network due to its sensing and monitoring application nature; nodes need to be aware of their own locations when reporting their sensing data; the data are usually sent back to a known "sink" location. The node location information can be obtained by prior configuration, by the Global Positioning System (GPS) receiver, or through some sensor self-configuring localization mechanisms such as [29–31].

Each network node is equipped with energy renewable batteries that can harvest energies from their working environment [6–8, 32].

A MAC protocol that allows retransmission is used, such as 802.11 [33]. The 802.11 ACK mechanism resends lost data frames, making all but the worst 802.11 links appear loss-free to the network layer.

Each node is informed with its own and its one-hop neighbors' battery residual energy level and the short-term energy harvesting rate, periodically. The residual energy in a battery can be estimated from its discharge function and measured voltage supplied [2]. Neighbor nodes exchange these information with each other by piggybacking them in the periodically broadcast "Hello" messages.

The network is dense enough so that no communication voids[1] exist. Mechanisms such as FACE routing [15] or perimeter forwarding in GPSR [16] can be applied to deal with the communication void problem but it is beyond the scope of this paper.

3.2 Link quality estimation

We denote the Frame Delivery Ratio (FDR)[2] from a node i to its neighbor j, FDR_{ij}. It is measured using "Hello" messages[3] which are broadcast periodically every τ time unit. Because the probes are broadcast, 802.11 does not acknowledge or retransmit them.

Two events will drive the updating of FDR_{ij} on node j: one is the periodical updating event set by the node, for example, every t_u seconds j will update FDR_{ij}. We denote this event as T; the other is the event that j receives a "Hello" packet from i. We denote this event as H.

Exponentially Weighted Moving Average (EWMA) function [34] is used as the link quality estimation algorithm which is often used in statistical process control applications. Let FDR_{ij} be the current estimation made by node j,

[1] When the forwarding node is distance-wise closest to the destination than any of its neighbors, but has no direct connection to the destination to deliver the packets, a communication void happens.

[2] We use Frame Delivery Ratio instead of Packet Delivery Ratio here to differentiate the data delivery ratio observed from the MAC layer and the network layer. As mentioned before, due to the lossy links, some MAC protocols such as 802.11 retransmit lost data frames to guarantee high delivery ratio at the network layer. That is, a successful packet transmission at the network layer may cause a number of transmissions (including retransmissions) at the MAC layer.

[3] In our proposed protocols, "Hello" message is used for both exchanging neighbor nodes' information and probing link quality.

Table 1 Pseudocode of EWMA

For node j:
When H event happens
$N_m = current_{Seg} - last_{Seg} - 1$
$last_{Seg} = current_{Seg}$
$lastHello$ = current time
$l = Max(N_m - N_g, 0)$
$N_g = 0$
$FDR_{ij} = FDR_{ij} \cdot \gamma^{l+1} + (1-\gamma)$
When T event happens
N_g =($current\ time - lastHello$) $\times \frac{1}{\tau}$
$l = N_g$
$FDR_{ij} = FDR_{ij} \cdot \gamma^{l}$

$lastHello$ be the time stamp of the last event H, N_m be the number of known missed "Hello" packets between the current event H and last event H based on sequence number difference, and N_g be a guess on the number of missed packets based on "Hello" message broadcast frequency $\frac{1}{\tau}$ over a time window between the current T event and last H or T event. N_m and N_g are initialized to be 0, and FDR_{ij} is initialized to be 1.

This technique allows j to measure FDR_{ij} and i to measure FDR_{ji}. Each probe sent by a node i contains FDR measured by i from each of its neighbors N_i during the last period of time. Then each neighbor of i, N_i, gets the FDR to i whenever it receives a probe from i.

The pseudocode of EWMA algorithm for node j to estimate FDR_{ij} is described in Table 1, where $current_{Seg}$ and $last_{Seg}$ denote the sequence numbers of the current received "Hello" message and the last received "Hello" message respectively, and $0 < \gamma < 1$ be the tunable parameter.

3.3 Energy consumption model

In this paper, the cost for a node to send or receive a packet is modelled as a linear function similar to [35]. There is a fixed cost associated with channel acquisition and an incremental cost proportional to the size of the packet:

$$Cost = c \times S_{pkt} + b \tag{1}$$

Where c denotes the energy needed for sending or receiving one byte of data, S_{pkt} denotes the size of the data in bytes and b is a constant. In this paper, we only consider the energy consumption when a node sends or receives data as most energy aware routing protocols do.

3.4 Energy harvesting model

Depending on the deployment conditions, such as whether or not directly exposed to sun light, the intensity of the sun light, the speed of air flow and so on, there is an uncertainty associated with environmental energy harvesting capability. We use a random process to model the energy harvesting rate of node i. We model the mean harvesting rate with a uniformly distributed random variable with mean μ_i, varying between $P_{i_{min}}$ and $P_{i_{max}}$. The energy harvesting capability is not homogeneous at all nodes. In addition, energy collected by the scavengers can be stored in some energy reservoirs such as batteries, fuel cells, capacitors, etc. However there is a capacity limit of such an energy reservoir, beyond which environmentally available energy cannot be stored. We use constant E_b to denote such a capacity limit for each node.

3.5 Protocol description

In our routing protocols, each node locally maintains its one-hop neighbors' information such as the neighbor's location, residual energy, energy harvesting rate, energy consuming rate, and wireless link quality (in terms of FDR). We assume that node i is forwarding a packet M, whose destination is D. Node i forwards M progressively towards the destination, while at the same time tries to balance the energy consumption across all its forwarding candidates N_i. We propose two local cost metric based protocols to achieve the goals.

3.5.1 GREES-L

Node i forwards the packet to the neighbor that minimizes the cost $C_L(N_i, D)$ which is defined as follows:

$$C_L(N_i, D) = \frac{1}{\alpha \cdot NPRO(i, N_i, D) + (1-\alpha) \cdot NE(N_i)} \tag{2}$$

where $0 < \alpha < 1$ is a tunable weight, $NPRO(i, N_i, D)$ is the normalized progressive distance per data frame from i to N_i towards D, and $NE(N_i)$ is the normalized effective energy on node N_i. $NPRO(i, N_i, D)$ is defined as follows:

$$NPRO(i, N_i, D) = \frac{PRO(i, N_i, D)}{Max\{PRO(i, N_i, D)\}} \tag{3}$$

where

$$PRO(i, N_i, D) = (Dist(i, D) - Dist(N_i, D)) \cdot FDR_{iN_i} \cdot FDR_{N_i i} \tag{4}$$

and $Max\{PRO(i, N_i, D)\}$ is the maximum PRO achieved by the forwarding candidates of node i. The $Dist(i, D)$ and $Dist(N_i, D)$ are the Euclidean distances between i and D and N_i and D respectively. So $(Dist(i, D) - Dist(N_i, D))$ is the packet advancement to the destination when the packet is forwarded from i to N_i.

$NE(N_i)$ is defined as follows:

$$NE(N_i) = \frac{E(N_i)}{Max\{E(N_i)\}} \tag{5}$$

where

$$E(N_i) = \beta \cdot (\mu_{N_i} - \psi_{N_i}) \cdot (t_c - t_l) + E_r(N_i) \tag{6}$$

and $Max\{E(N_i)\}$ is the maximum E achieved by the forwarding candidates of node i.

In Eq. (6), β is a tunable weight. μ_{N_i} is the last received expected energy harvesting rate information on node N_i by node i. ψ_{N_i} is the last received expected energy consuming rate information on node N_i by node i. t_c is the time when the node i is forwarding the packet. t_l is the last time when "Hello" message broadcast by N_i is heard by i, and μ_{N_i} and $E_r(N_i)$ are updated. ψ_{N_i} is updated every τ ("Hello" interval) at node N_i according to Eq. (7) when it broadcasts "Hello" message.

$$\psi_{N_i} = \frac{E_{c_\tau}(N_i)}{\tau} \tag{7}$$

where $E_{c_\tau}(N_i)$ is the energy consumed in the last interval τ.

Note that due to the lossy wireless channel, the updated information, such as μ_{N_i}, ψ_{N_i} and $E_r(N_i)$, may not be received by node i every τ. So the energy availability estimation $E(N_i)$ to the neighbor with worse $FDR_{N_i i}$ is less accurate than the neighbor with better $FDR_{N_i i}$. However this inaccuracy will not affect the next hop selection much if μ_{N_i} and ψ_{N_i} do not change much in the interval (t_l, t_c). Furthermore the worse the $FDR_{N_i i}$ is, the smaller the $PRO(i, N_i, D)$ is. So the probability of choosing N_i with low $FDR_{N_i i}$ as the next hop will become lower according to Eq. (2).

The rationale to define and minimize the cost function in Eq. (2) is as follows. Minimizing the cost in Eq. (2) is equivalent to maximizing the denominator. The denominator is a linear combination of two parts. The first part is $NPRO(i, N_i, D)$ which represents how much progress one frame can make towards the destination. In Eq. (4), the factor $FDR_{iN_i} \cdot FDR_{N_i i}$ is the inverse of the ETX (expected transmission count) defined in [21]. The physical meaning of Eq. (4) is the expected progress towards the destination per packet transmission. Maximizing it means maximizing the efficiency of transmitting a packet. When the transmission power is fixed, maximizing Eq. (4) also decreases the energy consumed per packet, as each transmission or retransmission increases a node's energy consumption. The second part is $NE(N_i)$ which represents the estimated energy availability on node N_i. From Eq. (6), we know the energy availability is represented by the linear combination of harvesting energy, consuming energy and the residual energy on the battery. The key difference from the traditional energy aware routing proposed in [2] which only considers the residual energy on nodes is that we also consider the environmental energy. So Eq. (2) is one way to balance the importance of progress per packet transmission (related to delay and energy consumption), energy replenishment and residual energy (related to load balancing).

Suppose that each neighbor of node i has the same energy harvesting rate and the same residual energy, node i will forward the packets to the neighbor with larger *PRO* to the destination.

In an environment where the energy source distribution is heterogeneous, the defined cost function in Eq. (2) will direct traffic to nodes with a faster energy renewal rate. Consider node i's neighbors having similar residual energy as well as similar *PRO* to the destination. Among these neighbors, the one which can replenish its battery at a higher rate will advertise a cheaper cost and will be selected as the next hop of node i.

When $\alpha = 1$, GREES-L degenerates to geographic routing similar to [19]. When $\alpha = \beta = 0$, GREES-L degenerates to traditional energy aware routing based on residual energy only similar to [2].

In this paper, we assume there is no communication voids, so there is always at least one neighbor of node i satisfying $PRO(i, N_i, D) > 0$. We only consider the neighbors with $FDR_{iN_i} > 0.2$ and $FDR_{N_i i} > 0.2$ as the candidates of node i's next hop, since it will cause a lot of retransmissions if we choose neighbors having bad link quality from/to node i. Retransmissions will not only consume sender's energy but also increase the interference to other nodes. When $E(N_i)$ in Eq. (6) is smaller than $(2 \cdot Cost)$ in Eq. (1), N_i will not be selected as the next hop of node i, since it does not have enough energy to receive and transmit a packet.

3.5.2 GREES-M

GREES-L uses linear combination to balance the geographical advance efficiency per packet transmission and the energy availability on receiving nodes, while GREES-M uses multiplication to balance these factors. The local cost function $C_M(N_i, D)$ is defined as follows:

$$C_M(N_i, D) = \frac{E_b(N_i) \cdot \eta^{\lambda_{N_i}}}{log\eta \cdot (\mu_{N_i} + \epsilon) \cdot PRO(i, N_i, D)} \tag{8}$$

where ϵ and η are appropriately chosen constants, $E_b(N_i)$ is the battery capacity, $PRO(i, N_i, D)$ is defined in Eq. (4) and λ_{N_i} is the fraction of energy used at node N_i defined in Eq. (9).

$$\lambda_{N_i} = \frac{E_b(N_i) - E_r(N_i)}{E_b(N_i)} \tag{9}$$

Node i forwards the packet to the neighbor that minimizes the local cost $C_M(N_i, D)$. Note that the cost function is different from the one in [11] in that we take into account the link quality and packet progress efficiency by using the factor $PRO(i, N_i, D)$.

The rationale for minimizing the cost function Eq. (8) is as follows. Note that the cost function is an exponential function of the nodal residual energy, an inversely linear function of the replenishment rate and the expected geographical progress per packet transmission. So Eq. (8) is another way to balance the importance of progress per packet transmission (related to delay and energy consumption), energy replenishment and residual energy (related to load balancing).

This cost function also directs traffic to the neighbor with larger *PRO* to the destination when neighbors have similar residual battery energy and environmental energy harvesting rate, and directs traffic to the neighbor with larger environmental energy harvesting rate when neighbors have similar residual battery energy level and *PRO*.

Note that even though $E_b(N_i)$ is in the numerator in Eq. (8), it does not imply that nodes with larger battery capacity are assigned a higher cost. The reason is that $E_b(N_i)$ is also embedded in the exponential cost metric $\eta^{\lambda_{N_i}}$ where λ_{N_i} is defined in Eq. (9). The introduction of ϵ accounts for the situation when nodes are not harvesting energy and $\mu_{N_i} = 0$.

The cost should be positive, which means *PRO* should be larger than zero. Then this cost function implicitly eliminates the neighbors that give negative progress to the destination. The candidate neighbor selection criteria is the same as GREES-L.

4 Performance evaluation

4.1 Simulation setup

All the simulations are implemented within the GloMoSim library [36], which is a scalable simulation environment for wireless network systems. The simulated sensor network has $N = 196$ stationary nodes uniformly distributed in a $d \times d$ m^2 square region, with nodes having identical fixed transmission power. We use $d = 250, 210, 180, 160$ to achieve various node densities in terms of 10, 15, 20, 25 neighbors per node on average. To simulate a randomly lossy channel, we assume Ground Reflection (Two-Ray) path loss model and Ricean fading model [37] for signal propagation. The packet reception decision is based on the SNR threshold. When the SNR is larger than a defined threshold, the signal is received without error. Otherwise the packet is dropped. We set proper parameters to make the maximum transmission range as 35 m. EWMA, described in Section 3.2, is used as the link estimation algorithm, where γ is chosen to be 0.9. IEEE 802.11 [33] is used as the MAC layer protocol. Each node was initialized with a fixed amount of energy/battery reserve (E_bmJ) before network deployment. The energy consumption model is described in Section 3.3, where $c = 1.9\,\mu$J/byte and $b = 450\,\mu$J for sending packets and $b = 260\,\mu$J for receiving packets. The energy harvesting model is described in Section 3.4. Three nodal energy harvesting rates are assumed in Table 2. Each node's harvesting rate is randomly chosen to be one of the three levels and is fixed on the level in one simulation run. We apply two types of application traffic: (1) peer-to-peer application traffic, which consists of fifteen randomly chosen communication pairs in the simulation area, and (2) multiple-to-one application traffic, which consists of fifteen application sessions from randomly selected 15 nodes to the sink node at the center of the simulation area. The sources are CBR (constant bit rate) with one packet per second and each packet being 512 bytes long. Each point in the plotted results represents an average of ten simulation runs with different seeds.

Table 2 Level of energy harvesting rate

	High	Medium	Low
$P_{i_{min}}$ (mw)	10	1	0.1
$P_{i_{max}}$ (mw)	20	5	1

4.2 Evaluation metrics

We define the following two metrics to evaluate the energy efficiency performance of the proposed routing protocols.

- *Mean residual energy.* This metric calculates the average residual energy at the end of simulation for all the sensor nodes. It is an indicator of energy efficiency in the sense that it represents the level of remaining energy in the network. The higher the value is, the more the energy remains in the network, and the better the performance is. Note that due to the presence of the renewable energy sources, this metric cannot be replaced by a metric that measures the total energy consumed. A better routing protocol with renewable energy supply should achieve better residual energy when total energy consumption is the same or even higher.
- *Standard deviation of residual energy.* This metric measures the standard deviation of the residual energy of all nodes. This quantity indicates how well the traffic load/energy consumption is distributed among nodes. The smaller the value is, the better the capability the routing protocol has in balancing the energy consumption.

The following performance metrics are also measured to evaluate the quality of service provided by the proposed routing protocols.

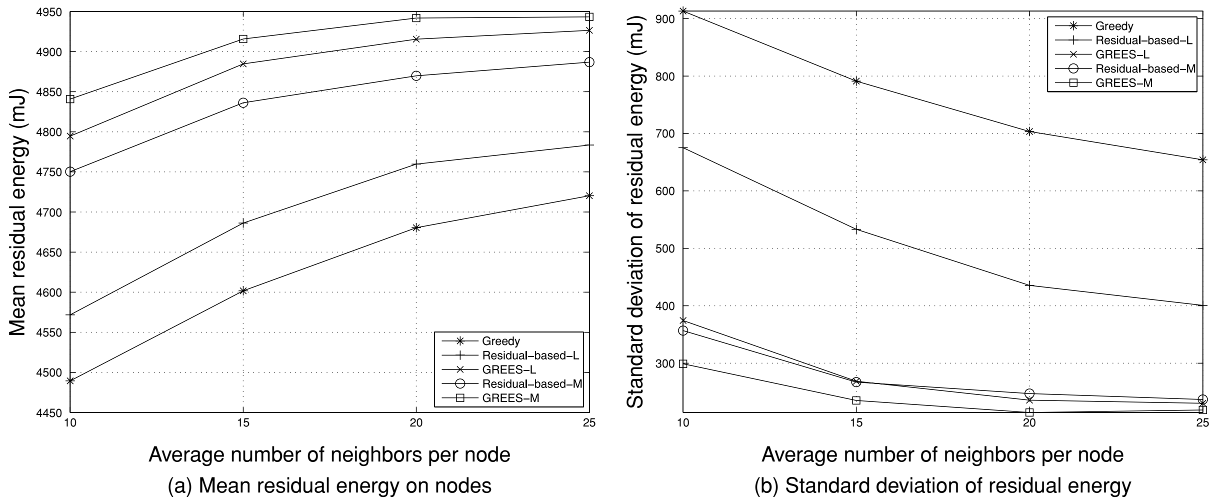


Fig. 2 Mean residual energy on nodes and their deviation at the end of the simulation under randomly distributed peer-to-peer traffic vs. network density

- *Normalized end-to-end throughput.* This metric is measured in bit-meters per second (bmps) as in [38]. It is calculated as in Eq. (10),

$$T(S, D) = \frac{N_{delivered} \cdot S_{pkt} \cdot Dist(S, D)}{t_{session}} \tag{10}$$

where $T(S, D)$ denotes the normalized throughput from source node S to destination node D, $N_{delivered}$ denotes the number of packets successfully delivered from S to D in the communication session, S_{pkt} denotes the packet size in bit, $Dist(S, D)$ denotes the Euclidean distance between S and D, and $t_{session}$ denotes the communication session duration from S to D in second. We account for the distance factor, because the throughput is indeed relative to the distance between the communication pair due to the lossy property of multi-hop wireless links in wireless sensor networks.

- *Normalized end-to-end delay.* It is measured as per packet delay from S to D over $Dist(S, D)$ in second per packet-meter (sppm), as the delay is also proportional to the distance between the communication pair.

4.3 Simulation results and analysis

4.3.1 Peer-to-peer traffic

Figures 2 and 3 show the simulation results under randomly distributed peer-to-peer application traffic. In this simulation, we set the "Hello" interval τ to 50 s, α in Eq. (2) to 0.5 for GREES-L, the battery capacity E_b to 5,000 mJ, β in Eq. (6) to 40, η to 100,000 and ϵ to 0.3 in Eq. (8) for GREES-M. In the figures, "Greedy" denotes the geographic routing without energy awareness but taking into account the wireless channel conditions, which is an extreme situation for GREES-L by setting α to 1 in Eq. (2). "Residual-based-L" denotes the

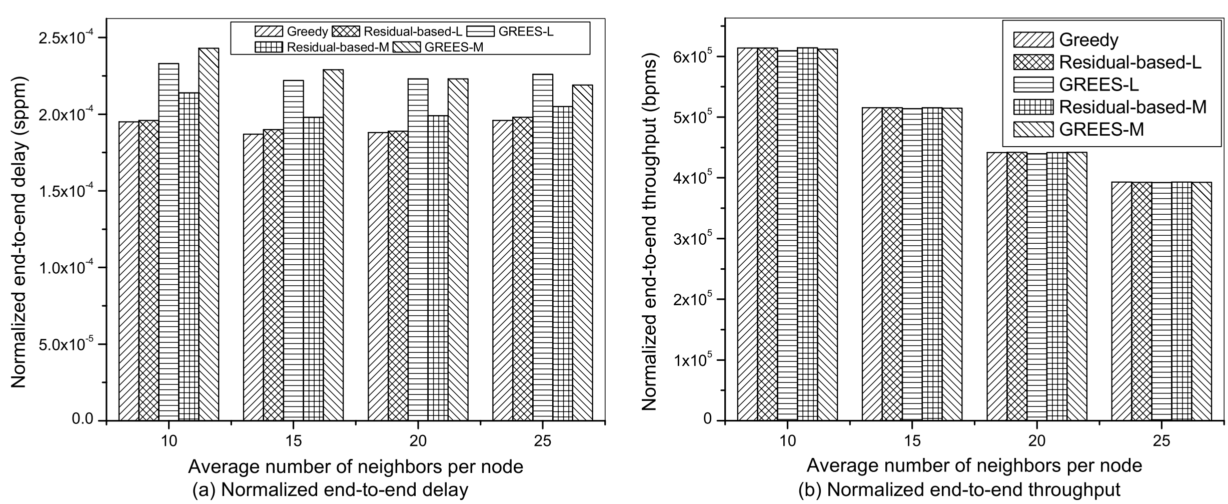


Fig. 3 Normalized end-to-end delay and throughput under randomly distributed peer-to-peer traffic vs. network density

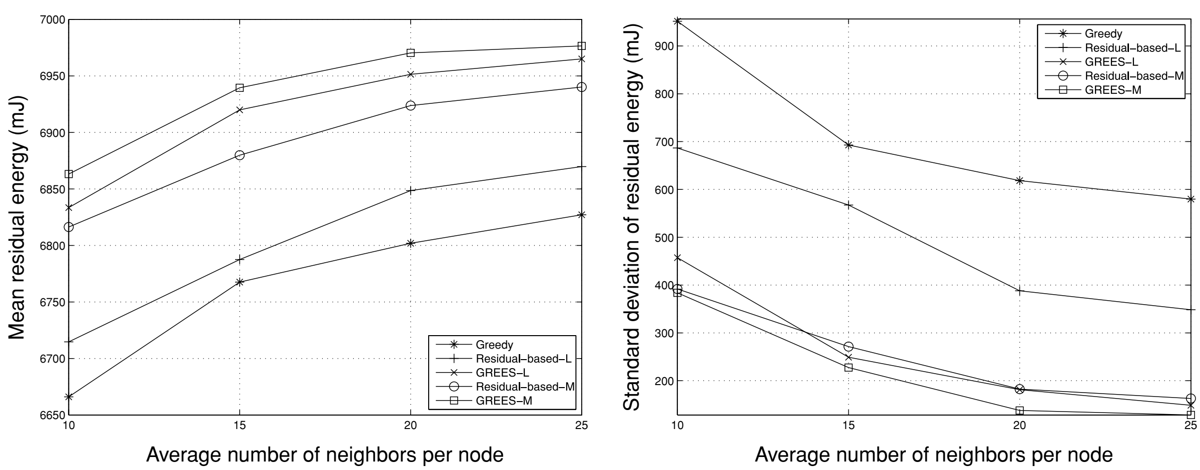
energy aware routing protocol that only considers the residual energy level on nodes, which is also an extreme situation of GREES-L by setting β in Eq. (6) to 0. "Residual-based-M", corresponding to GREES-M, denotes the energy aware routing protocol that only considers the residual energy level on nodes, which is just by eliminating the factor $(\mu_{N_i} + \epsilon)$ in Eq. (8).

Figure 2 shows that under randomly distributed peer-to-peer application traffic, (a) Both GREES-L and GREES-M are more energy efficient than the corresponding residual energy based protocols in terms of having higher mean residual energy and smaller standard deviation of residual energy; (b) GREES-M performs better than GREES-L on efficiency and load balancing; (c) The "Greedy" routing without energy awareness has the lowest mean residual energy and largest standard deviation of residual energy.

This results can be explained by the fact that GREES-L and GREES-M take into account the environmental energy harvesting rate as well as the residual energy on node, so they have more accurate energy availability estimation than the corresponding residual energy based protocols, therefore they are able to distribute the load better based on the energy level. Since "Greedy" routing considers neither the residual energy on node nor environmental energy harvesting, it has the worst performance on energy efficiency and load balancing. It is worth to mention that if there is no environmental energy supply, "Greedy" routing may achieve high mean residual energy, since it locally maximizes *PRO* to the destination. In our model, the transmission power is fixed, so maximizing the progress per packet transmission is equivalent to maximizing the progress per packet per unit of energy consumption. However, when there is environmental energy supply, it is not necessary to maximize the *PRO* for every packet. Some packets can be routed to the neighbor that makes smaller *PRO* but has more energy availability in order to avoid overusing some node and make good use of the environmental energy on some other nodes.

Another observation from Fig. 2 is that the more densely the nodes are deployed, the more energy remained on nodes, and the smaller the standard deviation is. Because when the nodes are closer to each other, the hop counts between the source and destination pairs become smaller, then the required energy for delivering one packet from the source to the destination is reduced, so the mean residual energy on nodes increases. Furthermore, when network is denser, the number of paths between the communication pairs increases, each node has more choices of the next hop to distribute traffic load, and the result is the decreased energy consumption variance among all the nodes.

The QoS performance of the five protocols under different network densities are shown in Fig. 3. We can see that GREES-L and GREES-M have longer delay than the corresponding residual energy based protocols since in order to achieve better load balancing, some packets may travel along some links of worse quality or travel longer hops to get to the destination. However the delay performance is not compromised much. In our simulation, GREES-L has 19% longer delay than the Residual-based-L and GREES-M has 14% longer delay than the Residual-based-M. The delay performance is not changed much with network density, as we already normalized the delay by dividing it by distance. The throughput performance is nearly the same for all the five protocols under different network density. It indicates that although some packets spend a little more time travelling to the destination, the packet delivery ratio is not compromised at all. Throughput is smaller when nodes are closer (denser) since the throughput is normalized by multiplying the source-destination distance.



(a) Mean residual energy on nodes (b) Standard deviation of residual energy

Fig. 4 Mean residual energy on nodes and their deviation at the end of the simulation under randomly distributed multiple-to-one traffic with sink at the center vs. network density

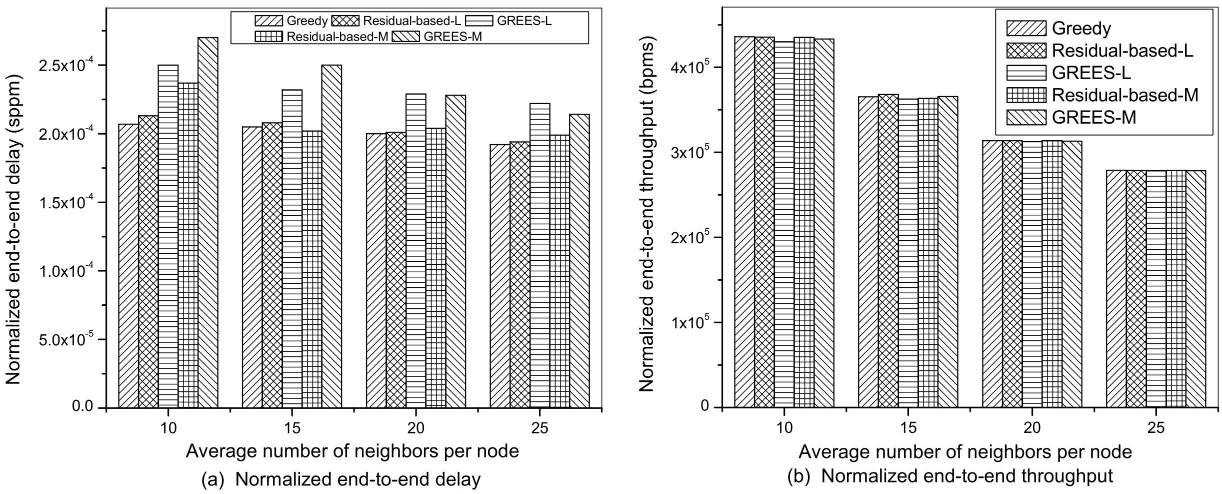


Fig. 5 Normalized end-to-end delay and throughput under randomly distributed multiple-to-one application traffic with sink at the center vs. network density

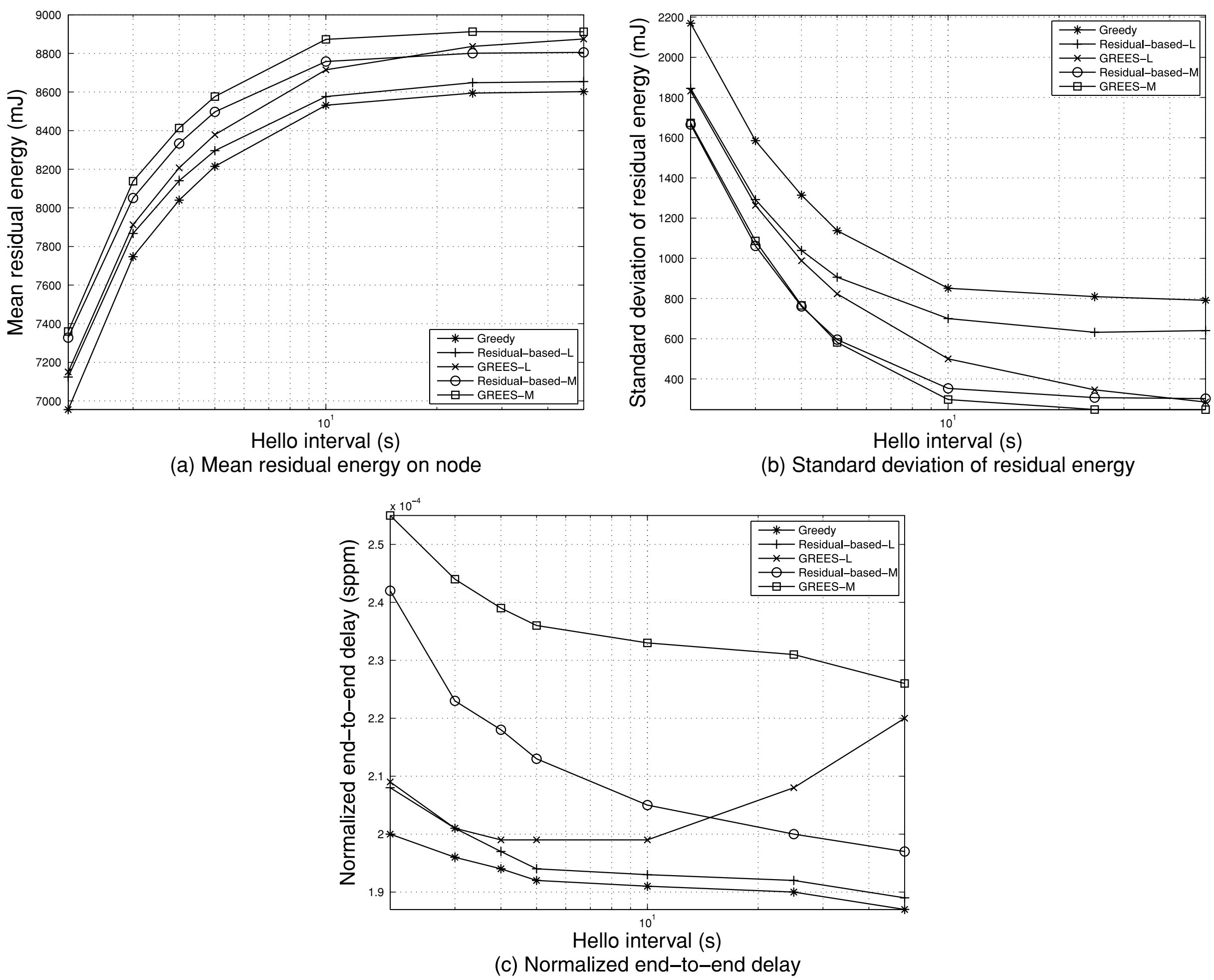


Fig. 6 Simulation results under randomly distributed peer-to-peer application traffic with different “Hello” intervals

4.3.2 Multiple-to-one traffic

Figures 4 and 5 show the simulation results under randomly distributed multiple-to-one application traffic. The simulation settings are the same as the peer-to-peer case, except that the communication pattern is from sensor nodes to the sink which is located at the center of the network, and the battery capacity is set to 7,000 mJ to accommodate the more demanding energy consumption of nodes close to the sink. The sink is not energy constrained.

Figure 4 shows the same trend as Fig. 2 that both GREES-L and GREES-M achieve better energy efficiency and load balancing than the corresponding residual energy based protocols under multiple-to-one application traffic. The reason is the same as explained in Section 4.3.1.

Figure 5 also shows the same trend as in Fig. 3 that both GREES-L and GREES-M exhibit graceful degradation on end-to-end delay but do not compromise the end-to-end throughput performance.

4.3.3 The effect of "Hello" interval

The results shown in this section are for uniformly distributed peer-to-peer application traffic. The simulation settings are similar to the simulation in Section 4.3.1, except that the average number of neighbors per node is fixed on 15, battery capacity is 9,000 mJ and $\beta = 60$. We vary the "Hello" interval from 2 s to 50 s. As shown in Fig. 6(a), the mean residual energy on nodes increases when the "Hello" interval increases. When the "Hello" interval is small, the energy efficiency and load balancing performance of GREES-L and GREES-M are nearly the same as the corresponding residual energy based protocols, especially when "Hello" interval is smaller than 3 s, as the residual energy information on nodes reflects the energy availability more accurately when the nodal information is exchanged more frequently. The reasoning also applies to the observation in Fig. 6(b) that when the "Hello" interval is small, the performance difference between GREESs and the corresponding residual energy based protocols is not obvious. Figure 6(c) shows the end-to-end delay performance. Generally the delay decreases as the "Hello" interval increases, except for GREES-L when "Hello" interval is larger than 10 s. The reason behind this result is that the energy availability estimation in Eq. (6) may play a more important role when the "Hello" interval is larger than a threshold, then the packets are distributed more evenly and travel longer hops. This can be seen in Fig. 6(a) that the mean residual energy is still increasing when "Hello" interval is larger than 10 s for GREES-L while other protocols remains nearly unchanged. Figure 6(b) also shows that the standard deviation of residual energy is still decreasing for GREES-L when "Hello" interval is larger than 10 s while other protocols remains nearly unchanged. The throughput performance is not shown here since all the five protocols exhibit almost the same throughput performance. These results imply that the information from neighbors does not need to be exchanged too frequently. The reduced broadcast frequency may help to reduce interference from local broadcast as well as to reduce energy consumption for transmitting and receiving broadcast messages.

5 Conclusion and future work

We proposed two energy aware geographic routing protocols, GREES-L and GREES-M, which make routing decision locally by jointly taking into account the realistic wireless channel condition, packet progress to the destination, the residual battery energy level of the node, and the environmental energy supply. The performance of the proposed protocols are evaluated and compared with the corresponding residual energy based protocols and "Greedy" routing protocols under different traffic patterns. Simulation results show that GREES-L and GREES-M are more energy efficient than the corresponding residual energy based protocols and "Greedy" routing protocols in terms of achieving higher mean residual energy on nodes, and achieve better load balancing in terms of having smaller standard deviation of residual energy on nodes. GREES-L and GREES-M have graceful degradation on the performance of end-to-end delay, but do not compromise the end-to-end throughput performance. GREES-M performs better than GREES-L on energy efficiency and load balancing. Our future work is the theoretical analysis of the two protocols and a more comprehensive simulation study which will be focusing on the understanding and optimization of the tunable parameters under various practical situations.

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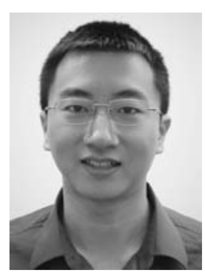

Kai Zeng received his B.E. degree in Communication Engineering and M.E. degree in Communication and Information System both from Huazhong University of Science and Technology, China, in 2001 and 2004, respectively. He is currently a Ph.D. student in the Electrical and Computer Engineering department at Worcester Polytechnic Institute. His research interests are in the areas of wireless ad hoc and sensor networks with emphases on energy-efficient protocol, cross-layer design, routing, and network security.

Kui Ren received his B. Eng. and M. Eng. both from Zhejiang University, China, in 1998 and 2001, respectively. He worked as a research assistant at Shanghai Institute of Microsystem and Information Technology, Chinese Academy of Sciences from March 2001 to January 2003, at Institute for Infocomm Research, Singapore from January 2003 to August 2003, and at Information and Communications University, South Korea from September 2003 to June 2004. Currently he is a PhD candidate in the ECE department at Worcester Polytechnic Institute. His research interests include ad hoc/sensor network security, wireless mesh network security, Internet security, and security and privacy in ubiquitous computing environments.

Wenjing Lou is an assistant professor in the Electrical and Computer Engineering department at Worcester Polytechnic Institute. She obtained her Ph.D. degree in Electrical and Computer Engineering from University of Florida in 2003. She received the M.A.Sc. degree from Nanyang Technological University, Singapore, in 1998, the M.E. degree and the B.E. degree in Computer Science and Engineering from Xi'an Jiaotong University, China, in 1996 and 1993 respectively. From December 1997 to July 1999, she worked as a Research Engineer in Network Technology Research Center, Nanyang Technological University. Her current research interests are in the areas of ad hoc and sensor networks, with emphases on network and system security and routing.

Patrick J. Moran received his MSEE from Carnegie Mellon University, 1993. He is currently the CTO and Founder of AirSprite Technologies Inc, and is driving the company to utilize advanced networking protocols for low-power wireless network systems. His interests include architecture, protocols and high performance implementation of emerging communication technologies. Patrick has been involved in deployment of communication and signal processing technologies since graduating from the University of Minn. in 1986. He holds several patents and publications relating to storage, medical and data processing information systems. He is a member of the IEEE.