Energy-Aware Geographic Routing in Lossy Wireless Sensor Networks with Environmental Energy Supply

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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-aware 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.**

I. Introduction

Wireless sensor networks 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 radio layer up to the transport layer and application layer.

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A common approach at the network layer to the energy efficiency problem is energy aware routing [1], [2], [3], [4], [5], [6], [7] in which sensors/nodes are assumed to be powered by batteries with limited/fixed capacity and then routing decisions are made based on the residual energy of each neighbor 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 [8], [9], [10], [11]. The first work to take environmental energy into account for routing was [12], followed by [13]. A distributed framework for the sensor network to adaptively learn its energy environment was presented in [12] and localized algorithms to use this information for task sharing among nodes was given. An example study of routing showed that the proposed framework is able to utilize the extra knowledge about the environment to increase system lifetime. Voigt, et al. [13] designed two solar-aware routing protocols that preferably route packets via solar powered nodes and showed that the routing protocols provide significant energy savings. Lin et al. [14] addressed the problem of power-aware routing with distributed energy replenishment for multihop wireless networks. A cost metric was proposed that considers node's battery residual energy, energy requirement for routing the packet along the path from source to destination, and energy replenishing rate. More comprehensive study is necessary to understand how this emerging battery technology may impact the energy efficient protocol design.

Another approach to energy efficiency is geographic routing [15], [16], [17], [18], [19] in which each node makes routing decision locally based on its own, its neighbors' and the destination's location information. Geographical routing technique is particularly applicable in wireless sensor networks because many sensing and monitoring applications of sensor networks require sensors to be aware of their physical locations. One of the advantages of geographic routing is that the routing overhead is minimized – neither route establishment flooding nor per-destination state is required. Other properties such as scalability, statelessness and low maintenance overhead also make it an attractive technique especially in large-scale sensor networks. 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 [15] chooses the neighbor closest to the destination as the next hop while MFR (Most Forward within Radius) [16] prefers the neighbor with the shortest projected distance (on the straight line joining the current node and the destination) to the destination. Greedy forwarding is very efficient but it can fail when a communication void happens, namely, when the current 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 number of techniques have been proposed, such as face/perimeter routing, to complement and enhance greedy forwarding [17], [18], [19] in the face of communication voids.

Several recent experimental studies on wireless adhoc and sensor networks [20], [21] have shown that wireless links can be highly unreliable and that this must be explicitly taken into account when considering higher-layer protocols. [22] showed the existence of a large "transitional region" where link quality has high variance. More recent works on geographic routing are aware of this more realistic lossy channel situation. Seada, et al. [23] articulated the distance–hop energy trade-off for geographic routing. They concluded that $PRR\ (Packet\ Reception\ Rate) \times Distance$ 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. [25] presented a more general framework called normalized advance (NADV) to minimize various types of link cost. Li, et al. [26] proposed a local power efficiency metric, $\frac{Prr^{*} \cdot D_{Proj}}{P^{*}_{Trans}+P_{elec}}$, for geographic routing such that at each step the transmitter picks as the next hop the neighbor for which this metric is maximized. The focus of these works is performance gain therefore none of them takes 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) [27], which uses energy awareness 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.

In this paper, we take a cross-layer 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, packets 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 network, energy, and traffic models, GREESs maintain higher mean residual energy of 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. We explain GREES-L and GREES-M in detail in Section II, and present and analyze our simulation results in Section III. Section IV presents our conclusions.

II. Geographic Routing with Environmental Energy Supply (GREES)

A. System Model

First we describe the system model on which our 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, or to a location specified in a broadcast query message. The distance between any two nodes, i and j, is the Euclidian distance between them, denoted as Dist(i,j).

Each network node is equipped with energy renewable batteries that can harvest energies from their working environment [8], [9], [10], [11].

A MAC protocol that allows retransmission is used, such as 802.11 [28]. 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 E_r and the short-term energy harvesting rate, μ_h, periodically. The residual energy in a battery can be estimated from its discharge function and measured voltage supplied [1]. 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 holes exist[1].

B. 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 [29] 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, $lastHello$ be the time stamp of the last H, N_m be the number of known missed "Hello" packets between the current H and last 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 w seconds. Then each neighbor of i, N_i, learns its FDR to i whenever it receives a probe from i.

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

TABLE I

PSEUDO CODE FOR EWMA

The pseudo code of node j using EWMA algorithm estimating FDR_{ij} is described in table I, where $current_{Seq}$ and $last_{Seq}$ denote the sequence numbers of the currently received "Hello" message and the last received "Hello" message respectively, and $0 < \gamma < 1$ be the weight parameter.

C. 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 [30], which represents a fixed cost associated with channel acquisition and an incremental cost proportional to the size of the packet:

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

where c denotes the energy needed for sending or receiving one byte of data, $Size_{pkt}$ 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.

D. 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 Pi_{min} and Pi_{max}. The energy harvesting capability is not homogeneous at all nodes. In addition, energy collected by

[1]Communication void problem is out of the scope of this paper.

[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 network layer. That is, one successful packet transmission at network layer may be the result of a number of transmissions (including retransmissions) at MAC layer.

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

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 battery capacity limit for each node.

E. Algorithm 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, 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, and at the same time tries to balance the energy consumption across all its neighbors N_i. We propose two local cost metric based protocols to achieve the goals.

1) GREES-L: Node i forwards the packet to the neighbor that minimizes the cost $C_L(N_i, D)$ value 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. $NPRO(i, N_i, D)$ and $NE(N_i)$ are defined as follows:

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

where

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

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

where

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

where β is a tunable weight. Recall that μ_{N_i} is the last received expected energy harvesting rate on node N_i by node i. ψ_{N_i} is the last received expected energy consuming rate 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 $E(N_i)$ of the neighbor with worse $FDR_{N_i i}$ is less accurate than that of the neighbor with better $FDR_{N_i i}$. However this non-accuracy will not affect the next hop selection much if μ_{N_i} and ψ_{N_i} do not change much between the interval $(t_c - t_l)$. 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 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 [20]. 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 we assume 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 [1] which only considers the residual energy on nodes is that we also consider the environmental energy. So Eq. (2) provides us with a clear guideline of how 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 their batteries at a higher rate will advertise a cheaper cost and will be selected as the next hop of node i.

When α=1, GREES-L degenerates to geographic routing similar to [25]. When α=β=0, GREES-L degenerates to traditional energy aware routing based on residual energy only similar to [1].

In this paper, we assume there is no holes, so there is always at least one neighbor of node i satisfying $PRO(i, N_i, D) > 0$. While selecting the next hop, 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 should not be selected as the next hop of node i, since it does not have enough energy to receive and transmit a packet.

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:

$$C_M(N_i, D) = \frac{1}{\eta^{\lambda_{N_i}} \cdot \mu_{N_i} \cdot PRO(i, N_i, D)} \quad (8)$$

where η is appropriately chosen constant, $E_{b_{N_i}}$ is the battery capacity, $PRO(i, N_i, D)$ is defined in Eq. (4) and λ_{N_i} is the fraction of energy remained at node N_i defined in Eq. (9).

$$\lambda_{N_i} = \frac{E_{r_{N_i}}}{E_{b_{N_i}}} \quad (9)$$

Node i forwards the packet to the neighbor that minimizes the local cost $C_M(N_i, D)$. The cost function is different from the one in [14] 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 inversely 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) provides us another guideline on how 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.

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

III. Performance Evaluation

A. Simulation Setup

All the simulations are implemented within the GloMoSim library [31], 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 neighborhood size of $10, 15, 20, 25$. To simulate a random lossy channel, we assume Ground Reflection (Two-Ray) path loss model and Ricean fading model [32] 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 $35m$. EWMA, described in section II-B, is used as the link estimation algorithm, where γ is chosen to be 0.9. IEEE 802.11 [28] is used as the MAC layer protocol. Each node was initialized with a fixed amount of energy/battery reserve (E_b mJ) before network deployment. The energy consumption model is described in section II-C, where $c = 1.9\mu J/byte$ for sending and receiving packets and $b = 450\mu J$ for sending packets and $b = 260\mu J$ for receiving packets. The energy harvesting model is described in section II-D. Three nodal energy harvesting rates are assumed in Table II. 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 15 randomly chosen communication pairs in the simulation area, and (2) multiple-to-one application traffic, which consists of 15 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

	High	Medium	Low
Min (mw)	10	1	0.1
Max (mw)	20	5	1

TABLE II
LEVEL OF ENERGY HARVESTING RATE

point in the plotted results represents an average of ten simulation runs with different seeds.

B. Evaluation Metrics

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

- *Mean residual energy (μ_r)*: 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 (σ_r)*: This metric measures the standard deviation of the residual energy of all nodes. This quantity indicates how evenly the remaining energy 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.

- *Normalized end-to-end throughput:* This metric is measured in bit-meters per second (bmps) as in [33]. It is calculated as in Eq. (10),

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

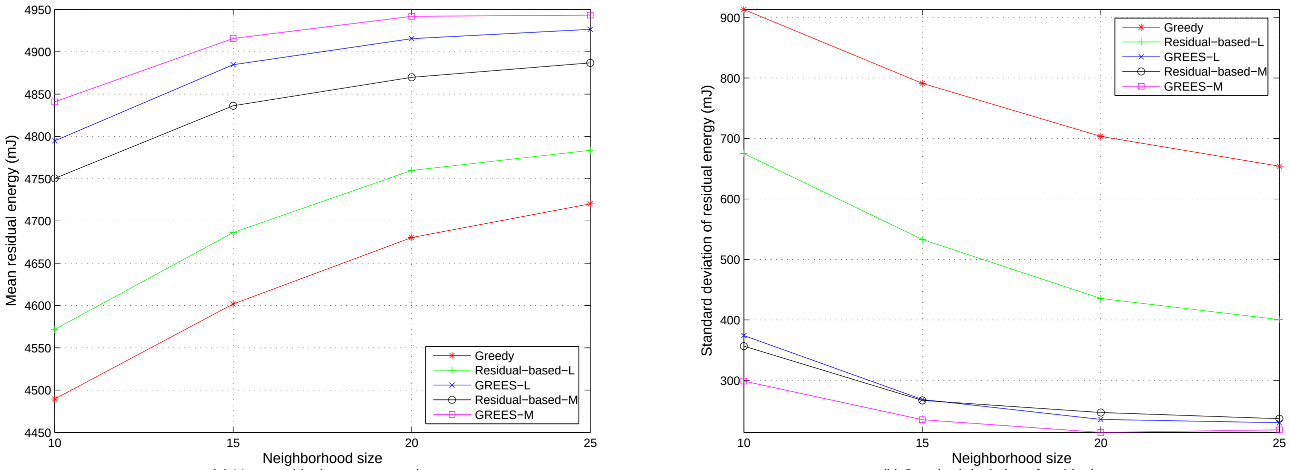
  where $T(S,D)$ denotes the normalized throughput from source node S to destination node D, $N_{delivered}$ denotes the number of packets delivered from S to D in the communication session, $Size_{pkt}$ denotes the packet size in bit, $Dist(S,D)$ denotes the Euclidean distance between S and D, and $t_{session}$ 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 the 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.

C. Simulations results and analysis

1) Peer-to-peer traffic: Figs. 1, 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 $50s$, α in Eq. (2) to 0.5 for GREES-L, the battery capacity E_b to $5,000mJ$, β in Eq. (6) to 40, and η to $100,000$ in Eq. (8) for GREES-M. The β is chosen as 40 to make the first part in the right side of Eq. (6) comparable to the second part $E_r(N_i)$ so that the energy changing rate (including harvesting and consuming rates) plays an effective role in Eq. (6). 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 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 μ_{N_i} in Eq. (8).

Fig. 1 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; and 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



(a) Mean residual energy on nodes

(b) Standard deviation of residual energy

Fig. 1. Simulation results under peer-to-peer traffic

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 packets. Some packets can be routed to the neighbor that makes smaller PRO but has more energy availability in order to avoid overusing some node. For example, suppose that node A has two neighbors B and C, and A is going to send ten packets to the destination D with one packet per second. B has a little larger PRO to D than C, but the expected energy consumption per packet transmission from A to B and A to C are the same. Assume B and C have the same energy harvesting rate of 1 unit of energy per second, and B and C consume the same energy, say 2 units, to receive a packet and forward the packet to their next hop. For "Greedy" routing, B is always chosen to relay the packets, then after relaying 10 packets, B will deplete 10 units of energy from its battery in the sense that it consumes 20 units for receiving and forwarding the packets while harvesting 10 units. C depletes 0 unit of energy and harvests 0 unit of energy because its battery is always fully charged. For energy aware routing, when B depletes its energy after sending several packets, the cost for B to forward the packet is increased according to Eqs. (2) and (8), then C will be chosen as the next-hop of A. When C is forwarding the packets, B will harvest energy from environment and recharge its battery, so after a while, the cost for B to forward the packet will be decreased, and B will be again selected as the next hop of A. Suppose the nodal information is exchanged every 2 second, B and C are alternately selected as the next hop of A. Then after relaying 10 packets (B relays 6 and C relays 4), B depletes 2 units of energy in the sense that it consumes 12 units for receiving and forwarding packets meanwhile harvesting 10 units, and C depletes 0 units in the sense that it consumes 8 units for receiving and forwarding packets meanwhile harvesting 8 units. That's the reason why energy aware routing protocols achieve better load balancing and at the same time achieve higher mean residual energy than "Greedy" routing protocol.

We further explain why GREES-L and GREES-M have better energy efficiency and load balancing than the corresponding residual energy based routing protocols. We still use the communication settings of the former example, except that C has already depleted 5 units of energy before the starting of the communication session, C has high energy harvesting rate of 4 units per second, while B has lower harvesting rate of 0.5 units per second. Suppose the battery capacity is 50 units and the nodal information is exchanged locally every 5 second. For residual energy based routing protocol, B will first be selected to relay packets. After five seconds, B depletes 7.5 units of energy in the sense that it consumes 10 units for communication meanwhile harvesting 2.5 units, and C will be fully charged. Then C is selected to relay the next five packets. At the end of the communication, B depletes 5 units since it harvests 2.5 units in the last 5 seconds, and C is fully charged because its energy harvesting rate is larger than the consuming rate. For GREES-L and GREES-M, C will be selected all the time according to Eqs. (2) and (8). Then at the end of

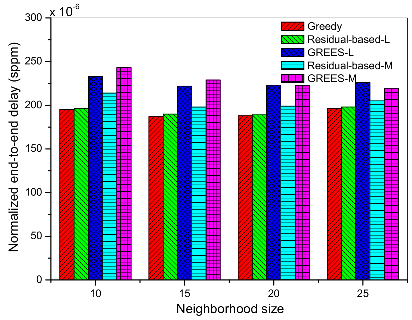


Fig. 2. Normalized end-to-end delay under randomly distributed peer-to-peer application traffic

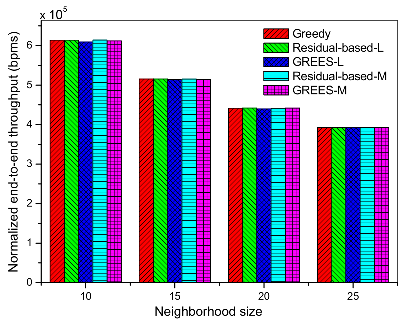


Fig. 3. Normalized end-to-end throughput under randomly distributed peer-to-peer application traffic

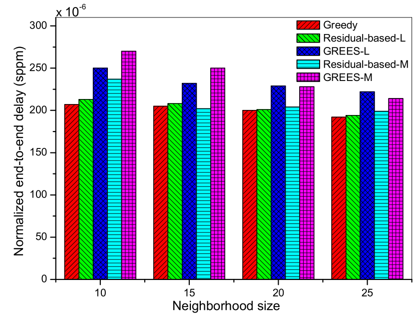


Fig. 5. Normalized end-to-end delay under randomly distributed multiple-to-one application traffic with sink at the center

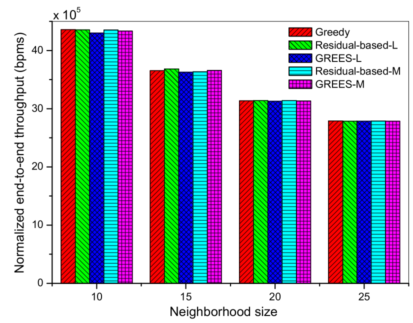


Fig. 6. Normalized end-to-end throughput under randomly distributed multiple-to-one application traffic with sink at the center

the communication, the batteries of B and C are both fully charged.

Figs. 2 and 3 show the QoS performance of the five protocols. 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 more 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 normalize the delay by dividing it by distance. The throughput performance is nearly the same for all the five protocols under different network density. It tells us 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.

2) Multiple-to-one traffic: Fig.4 shows the simulation results of energy efficiency and load balancing 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 in the center of the network, and the battery capacity is set to $7,000mJ$ to accommodate the more demanding energy consumption of nodes close to the sink. The sink is not energy constrained.

Fig. 4 shows the same trend as Fig. 1 does 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 III-C.1.

Figs. 5 and 6 also show the same trend as in Figs. 2 and 3 respectively 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.

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 III-C.1, except that the neighborhood size is fixed on 15, battery capacity is $9000mJ$ and $\beta = 60$. We vary the "Hello" interval from $2s$ to $50s$. As shown in Fig.7(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

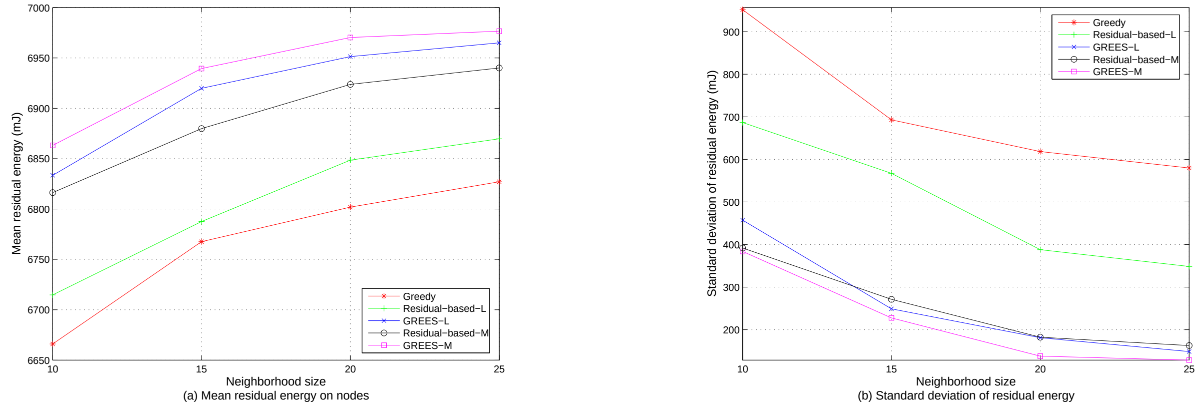


Fig. 4. Simulation results under multiple-to-one traffic with sink at the center

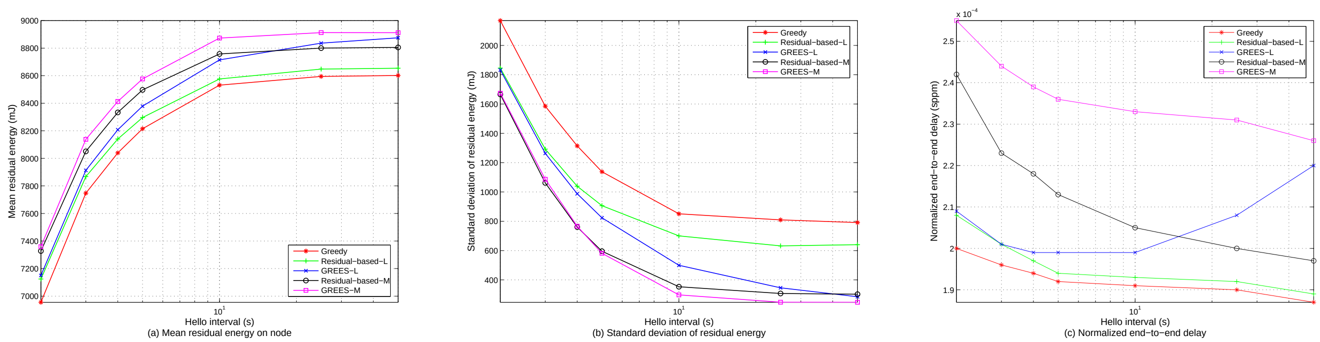


Fig. 7. Simulation results under randomly distributed peer-to-peer application traffic with different “Hello” intervals

of GREES-L and GREES-M are nearly the same as the corresponding residual energy based protocols, especially when “Hello” interval is smaller than $3s$, 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.7(b), when the “Hello” interval is small, the performance difference between GREESs and the corresponding residual energy based protocols is not obvious. Fig.7(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 $10s$. The reason behind that 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 more hops. This can be seen in Fig.7(a) that the mean residual energy is till increasing when “Hello” interval is larger than $10s$ for GREES-L while other protocols remains nearly unchanged. Fig.7(b) also shows that the standard deviation of residual energy is still decreasing for GREES-L when “Hello” interval is larger than $10s$ 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 neighborhood information does not need to be exchanged too frequently. The reduced broadcast frequency may help to reduce interference from local broadcast as well as reduce energy consumption for transmitting and receiving broadcast messages.

IV. 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 pattern. 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 that they achieve higher mean residual energy on nodes, and achieve more evenly distributed 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 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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