Q-Probabilistic Routing in Wireless Sensor Networks

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Abstract

Unpredictable topology changes, energy constraints and link unreliability make the information transmission a challenging problem in wireless sensor networks (WSN). Taking some ideas from machine learning methods, we propose a novel geographic routing algorithm for WSN, named Q-Probabilistic Routing (Q-PR), that makes intelligent routing decisions from the delayed reward of previous actions and the local interaction among neighbor nodes, by using reinforcement learning and a Bayesian decision model. Moreover, by considering the message importance embedded in the message itself, routing decisions can be adapted to traffic importance. Experimental results show that Q-PR becomes a routing policy that, as a function of the message importance, achieves a trade-off among the expected number of retransmissions (ETX), the successful delivery rate and the network lifetime.

1. Introduction and Challenges

Connecting a source node with a sink node through a route of lossy links in a WSN requires the cooperation among many intermediate nodes. Frequent and unpredictable topology changes as well as the severe energy constraints in sensors, make classical routing techniques fail in these environments.

A wide variety of routing algorithms for ad-hoc and sensor networks have been recently proposed [1]. Connection-based algorithms (both reactive and proactive) differentiate an initial route discovery phase to keep routing tables updated, after which packet forwarding takes place. Consequently, topology changes during the packet transmission phase force to stop forwarding and to start a new route discovery phase. Their performance strongly depends on the topology change frequency what makes them suitable only for very stable networks. Improvements for dynamic networks have been accomplished by “connectionless” [16] methods that carry out route discovery and packet forwarding as a whole, deciding the route at every hop. Search-based, constrained flooding and geographic routing strategies belong to this latter group.

The performance of search-based and geographic routing methods can be seriously affected by physical conditions: the delivery probability between nodes depends on factors such as the distance between them, interferences and collisions, and sending a message between two neighbor nodes may require more than one transmission [13], [4]. The increased robustness provided by flooding-based protocols (where each node individually makes the decision to forward or not) implies, however, an undesirable increment in energy consumption and in the chances of message collision.

A recent opportunistic approach in the context of geographic routing protocols has been proposed [4], [11] in order to manage channel conditions and topology changes. Basically, this approach relies on the fact that the actual forwarding node is chosen after the message has been transmitted among the candidates that successfully received it. It turns out, however, that the coordination between candidate nodes is not straightforward and should be carefully specified. Transmission priorities among candidates are established based on physical distance to destination regardless of the present network state [11] or based on the expected number of retransmissions (ETX) to destination [4], a knowledge that is estimated and distributed by a server at the network startup. Nonetheless, if network operation conditions change, this knowledge should be updated dynamically. Moreover, in a WSN, cost metrics such as node energy availability is also of major concern.

In this paper, we exploit the potential benefits of machine learning techniques to provide sensor nodes with the capability to learn from previous experiences, make routing decisions and adjust to future conditions. Learning reduces the amount of information stored, transmitted and updated, optimize the use of the local information available at nodes and provide a way to deal with uncertainty in the network state.

Our proposal stands on the idea that the cost metrics mentioned above can be learned and estimated from previous traffic patterns and the routing decisions can be updated accordingly. We explore an opportunistic-based routing policy that attempts to *learn* (i) from the delayed reward (or cost) of previous routing decisions and (ii) from information broadcasted by nodes to their respective neighbors. We will refer to it as Q-Probabilistic Routing (Q-PR).

The paper is organized as follows: Sect. 2 explains the

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basic idea underlying the Q-PR algorithm, Sect. 3 provides the details, Sect. 4 contains the experiments and Sect. 5 states some conclusions with some future research lines.

2. Q-PROBABILISTIC ROUTING: A BIG PICTURE

The Q-PR algorithm takes advantage of the broadcast nature of transmissions in WSN. The transmitter node sends a message to a group of potential forwarding nodes, though it is likely to be received only by some of them due to lossy links. The selection of the forwarding node results from the coordinated but individual decisions of the nodes in this subset.

Unlike conventional opportunistic routing, (i) the group of candidate nodes is enforced to be neighbors among themselves, what makes coordination easier and with reduced overhead, (ii) the cost metrics are neither a mere distance [11] nor an estimated ETX delivered by a server in the network tuning phase [4], but they are updated from the delayed reward of previously taken actions using a *reinforcement learning* (RL) rule, and (iii) the message transmission is conditioned to the individual node decisions.

The "Q" term stems from the Q-learning strategy in RL [6]. It has been formerly adapted to the routing problem in wired networks [8], but learning is only carried out on a one-to-one basis: when a forwarding node is selected, it replies to the previous node with its estimated cost metric to destination. Some recent applications of RL to routing in wireless networks [17], [5] follow a search-based approach and therefore, suffer from the same shortcomings. Unlike wired networks, a great advantage can be taken of the intrinsic broadcast nature of a wireless environment that favors the information spread and allows to easily disseminate a more up-to-date network state.

Finally, despite the routing objective in most routing protocols is fixed and independent on the message, embedding objectives into the message allows to apply general-purpose routing strategies that obtain QoS-aware protocols [16]. The Q-PR algorithm uses the importance value embedded in the message itself, to make node decisions about the message transmission. Next, the algorithm is described in depth.

3. THE Q-PROBABILISTIC ROUTING ALGORITHM

The Q-PR algorithm discovers the next hop of the actual route (a) as packets travel along the network (and not as a previous phase), (b) after the message has been sent (opportunistic approach), (c) using the geographic position (location-based routing [12]) and (d) making intelligent decisions at the nodes receiving the forwarding requests, based on local information as well as on the importance of message to be forwarded.

A. Wireless Sensor Network

Consider a *static* WSN with N regular source nodes N_i, $\{i = 1, \ldots, N\}$ and a destination node N_0 (sink node or access point). We assume that each node is aware of its position, the geographic position of the sink node and local information (state and position) of its neighbors. For details about how nodes can be provided with this information, see [10].

TABLE 1: LOCAL INFORMATION OF N_1'S NEIGHBOR NODES.

	Neighbor nodes N_j						
Local information at N_1	N_2	N_3	N_4	N_5	N_6	N_7	N_8
Distance to sink, D_{j0}	7	8	14	15	10	5	6
Delivery prob., $\widehat{P}_{D_{1j}}$	0.55	0.9	0.7	0.4	0.8	0.1	0.5
ETX to sink, $\widehat{Q}_1(j)$	2.5	5.2	20	23	25	2.1	4.1
Estimated Energy, $\widehat{E}_{1j}$	0.7	0.8	0.6	0.2	0.9	0.6	0.5

The neighbors of node N_i will be denoted by ϕ_i, and those closer to the access point than the node itself by ϕ_i^+. Unlike algorithms that consider neighbors to all nodes within a distance R (UDG, Unit Disc Graph model) regardless of the link quality, our algorithm is aware of the delivery probability within nodes. As pointed out in [13], the UDG can be improved and replaced by a more realistic model, where packet reception probability depends not only on the distance between nodes but also on other factors, such as interferences. Thus, we consider two nodes as neighbors if the (estimated) delivery probability between them is above a predefined threshold.

B. Node Information

As mentioned above, each node N_i knows its position, $\mathbf{z}_i$, that of the access point, $\mathbf{z}_0$, and that of its neighbors. Each node also keeps an estimate of the delivery probability with neighbor nodes. Following [14], we assume that the reception probability, $\alpha(x)$ as a function of distance, satisfies a log-normal shadowing model, given by

$$\alpha(x) = \begin{cases} 1 - \dfrac{1}{2}\left(\dfrac{x}{R}\right)^{2\beta} & \text{if } 0 \le x < R \\ \dfrac{1}{2}\left(2 - \dfrac{x}{R}\right)^{2\beta} & \text{if } R \le x < 2R \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

where β is the attenuation factor, and R is the distance such that $\alpha(R) = 0.5$. Delivery probability $\alpha(x)$ can be also approximated based on signal strengths or statistics from the number of messages sent and received between nodes.

As an example, consider the WSN in Fig. 1. Table 1 shows the local information gathered by node N_1, and Table 2 its second order neighbors. Node N_i is expected to know the following about each neighbor, N_j :

- $D_{j0} = \|\mathbf{z}_j - \mathbf{z}_0\|$: Euclidean distance to destination.
- $\widehat{P}_{D_{ij}} = \alpha(D_{ij})$, where D_{ij} is the distance between nodes N_i and N_j: Delivery probability between nodes.
- $\widehat{Q}_i(j)$: Estimation of the ETX to reach destination node N_0 from N_i through neighbor N_j.[1]
- $\widehat{E}_{ij}$: Estimation (by N_i, based on the number of overheard retransmissions) of the energy at node N_j.

C. Making a routing decision

1) Selecting forwarding candidates: Q-PR is a greedy position-based algorithm, based on the cost metric given by

[1]Note that the cost metric, commonly referred as Q-value in RL, is denoted here by $Q_i(j)$ and it refers to ETX.

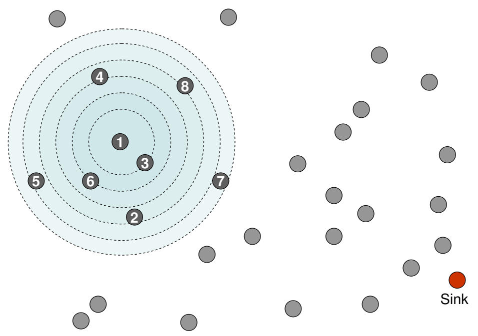


Fig. 1: Wireless sensor network scenario where node N_1 is responsible for forwarding a message to the sink node. N_1's neighbors are represented in the circular area and are those with delivery probability higher than a threshold.

TABLE 2: 2-HOP NEIGHBORS: NEIGHBORS OF N_1'S NEIGHBOR NODES.

Neighbor nodes						
N_2	N_3	N_4	N_5	N_6	N_7	N_8
N_2	N_2	N_1	N_6	N_5	N_2	N_1
N_3	N_4	N_3	N_2	N_2	N_3	N_3
N_6	N_8	N_6	N_1	N_4	N_1	N_7
N_7	N_7	N_8	...	N_3	N_8	N_4
N_5	N_1	...		N_1	...	...
...	N_5			...		
	N_6					

$CM = Q/P$, where Q is the expected number of retransmissions (ETX) to destination and P is the progress (by how much the distance to destination would be decreased) in that hop. Taking into account that ETX integrates energy consumption, link quality and delays, optimizing ETX [3] seems more suitable than minimizing the number of hops.

When node N_i receives a message, it is notified to be responsible (together with other neighbors of higher and/or lower priority) for forwarding it to the sink node. If higher priority nodes forward the message, node N_i will not do it. Otherwise, the node has to make a discard/transmit decision.

To do so, it proceeds as follows: (i) from the set of nodes closer to destination than itself, it selects the node minimizing the cost metric Q/P, and (ii) iteratively selects the best nodes among the remaining ones that fulfill the constrain of being neighbors of the previously selected candidates. This latter point assures that the set of candidate forwarding nodes can communicate among themselves. This subset of candidates selected by node N_i will be denoted as ϕ_i^*, $\{\phi_i^* \subset \phi_i^+\}$.

In the scenario previously described, with N_1 at 9 unit distance to destination (D_{10}=9), the subset $\phi_1^+ = \{N_2, N_3, N_7, N_8\}$. According to the cost metric in Table 3, the ordered set becomes $\{N_7, N_2, N_8, N_3\}$. However, according to Table 2, node N_8 is discarded since it is not neighbor of both previously selected candidate nodes, what results in $\phi_i^* = \{N_7, N_2, N_3\}$ with decreased order of optimality and therefore, priority to forward the message.

In order to get the compromise between route exploitation-exploration and following a common approach in RL methods [6], the actual forwarding node is selected at random among all neighbors, with a small probability ϵ.

TABLE 3: COST METRIC OF N_i'S NEIGHBOR NODES.

	$N_j \in \phi_1^+$			
Cost metric estimation for N_1	N_2	N_3	N_7	N_8
Distance to destination: $\|\mathbf{z}_j - \mathbf{z}_0\|$	7	8	5	6
ETX to Destination: $Q_1(j)$	2.5	5.2	2.1	4.1
ETX/Progress: $\frac{Q_1(j)}{\|\mathbf{z}_1 - \mathbf{z}_0\| - \|\mathbf{z}_j - \mathbf{z}_0\|}$	1.25	5.2	0.52	1.37

A special situation arises when the candidate set is empty (i.e. there are no progressing neighbors). In this case, a list of candidates, prioritized by the delivery probability, is created, placing the node from which the message is received at the end. The same applies when neighbor nodes become non-cooperative, but in this case selection as forwarder node the following in the original prioritized candidate list.

2) Transmit/discard decision: After selecting the set of candidate neighbor nodes, ϕ_i, a decision has to be made about forwarding the message to these nodes, taking into account the energy expense and the probabilities that they will eventually forward the message. Our decision model is a modified version of a preliminary model in [2], and is explained below:

Node i decisions will be based on:

- Single Transmission Energy: E_T
- Single Reception (or idle mode) Energy: E_{IR} (we assume equal energy expenses in reception and idle modes [15]). Unlike [2], here we assume more energy consumption in transmission than in reception (or idle) mode.
- Message Importance: I
- Candidate profiles, learnt from previous experiences

All these variables are grouped into an observation vector $\mathbf{x}$ and, based on it, the node decides whether to forward the message ($d = 1$) or not ($d = 0$), following a Bayesian decision approach with two hypothesis: $T = 0$ and $T = 1$, where:

$T = 0$, if no candidate node will forward the message (thus, saving energy to transmit more important messages).

$T = 1$, if at least one of the candidate nodes will forward the message.

If c_{ij} is the cost of deciding $d = i$ when $T = j$ (where $i, j \in \{0, 1\}$) we define: $c_{00} = E_{IR}$, $c_{01} = E_{IR}$, $c_{10} = E_T$ and $c_{11} = E_T - \gamma I$. Note that the cost of rejecting a forwarding request is the energy spent while keeping listening, and c_{11}, the cost of deciding to forward a message when there are candidates to retransmit, is reduced according to message importance I. Parameter γ modulates the trade-off between the transmission energy (cost) and the message importance (benefit), unlike the model in [2]. Nevertheless, the cost model proposed here has an illustrative purpose.

According to this, the risks (mean costs) associated to decide in favor to transmit or discard are given by

$$R(d = 1|\mathbf{x}) = E_T - \gamma I P(T = 1|\mathbf{x}) \quad (2)$$
$$R(d = 0|\mathbf{x}) = E_{IR} \quad (3)$$

respectively, and the minimum risk decision rule [20] is given by

$$P(T=1|\mathbf{x}) \underset{0}{\overset{1}{\gtrless}} \frac{E_T - E_{IR}}{\gamma I} \qquad (4)$$

The probability that candidate node N_i transmits a message depends on the decisions made by other candidate nodes with higher priority in the list. In order to decide whether to transmit or not, node N_i estimates the posterior probability of hypothesis $T=1$. Defining $P(F_j=1|\mathbf{x})$ as the posterior probability that N_j is able to forward the message and $P(T_j=1|\mathbf{x})$ as the posterior probability that N_j will definitely retransmit the message, we have

$$P(T=1|\mathbf{x}) = \sum_{N_j \in \phi_i^*} P(T_j=1|\mathbf{x}) \qquad (5)$$

where

$$P(T_j=1|\mathbf{x}) = P(F_j=1|\mathbf{x}) \prod_{\substack{N_k \in \phi_i^* \\ CM_k < CM_j}} P(F_k=0|\mathbf{x}) \qquad (6)$$

Note that $P(T_j=1|\mathbf{x})$ depends on the probability that higher priority nodes will not be able to transmit the message.

In order to compute Eq. (6), we will make the simplifying assumption that the probability that node N_i is able to forward a message is independent on the information available about any other node. Thus, nothing that the local information of node N_j is given by $\mathbf{x}_j = (\widehat{E}_{ij} \quad I \quad 1)$ (the last component is included for mathematical convenience), we can write

$$P(F_j=1|\mathbf{x}) = P(F_j=1|\mathbf{x}_j)\widehat{P}_{D_{ij}} \qquad (7)$$

where $\widehat{P}_{D_{ij}}$ is the estimated delivery probability.

Since a close-form expression for $(F_j=1|\mathbf{x}_j)$ is unknown, we will assume a logistic model

$$P(F_j=1|\mathbf{x}_j) = \frac{1}{1+\exp(-\mathbf{w}_j^T \mathbf{x}_j)} \qquad (8)$$

Then, rule (4) is applied using Eqs. (5), (6) and (8).

D. Learning from previous experiences

The information captured from the environment or from other nodes is used to update the Q values and parameters $\mathbf{w}$.

1) Updating local information via Reinforcement learning. Q-PR employs only local information in order to select the potential forwarding nodes for the next hop. Specifically, the expected number of retransmissions to destination is updated following a RL approach: whenever node N_j forwards a message, it broadcasts its estimated transmission count $Q_j(\phi_j^*)$ to all neighbor nodes. Any neighbor node N_i updates its Q-value to destination through node N_j as

$$Q_i(j) \leftarrow (1-\eta)Q_i(j) + \eta(Q_j(\phi_j^*) + q_{ij}) \qquad (9)$$

where η is the learning rate and q_{ij} the ETX to reach j from i. Though a decreasing η is usual in RL algorithms, we keep it constant for a fast adaptation to the dynamic network behavior.

The ETX from i to j can be estimated as

$$\widehat{q} = \sum_{k=1}^{\infty} k(1-\widehat{P}_{D_{ij}})^{(k-1)}\widehat{P}_{D_{ij}} = \frac{1}{\widehat{P}_{D_{ij}}} \qquad (10)$$

Note that $Q_i(j)$ depends on j, which is the eventual forwarding node. The ETX (over all candidate nodes) to sink node must be computed as a mean over all possible forwarders,

$$\widehat{Q}_i(\phi_i^*) = \frac{\sum_{N_j \in \phi_i^*} P(T_j=1|\mathbf{x})\mathrm{Q}_i(j)}{\sum_{N_j \in \phi_i^*} P(T_j=1|\mathbf{x})} \qquad (11)$$

Unlike RL algorithms that update the cost metric at node N_i with the minimum cost to destination, here we update it with an average cost since next forwarder is not known in advance.

2) Learning neighbor profile.

Each node estimates parameters $\mathbf{w}$ of the logistic neighbor profile in (8) without exchanging any information among nodes, but just by overhearing node retransmissions.

Defining $y_{ij} = P(F_j=1|\mathbf{x})$ and d_{ij} as the decision of node N_j to forward a message from node N_i, parameters $\mathbf{w}_j$ are estimated in order to minimize a loss function able to provide adequate estimates of the posterior probabilities to forward the message, such as the cross entropy loss function [9], commonly used in neural network training algorithms,

$$L(y_{ij}, d_{ij}) = -d_{ij}\ln y_{ij} - (1-d_{ij})\ln(1-y_{ij}) \qquad (12)$$

Applying stochastic gradient learning rule, node N_i computes

$$\mathbf{w}_j^{(k+1)} = \mathbf{w}_j^{(k)} + \mu(d_{ij}^{(k)} - y_{ij}^{(k)})\frac{\widehat{P}_{D_{ij}} - y_{ij}^{(k)}}{\widehat{P}_{D_{ij}}(1-y_{ij}^{(k)})}\mathbf{x}_j^{(k)} \qquad (13)$$

E. Updating information from statistics

Assuming that energy consumption in sensor networks is similar in reception and idle modes [15] and lower than energy consumed by transmissions, $\widehat{E}_{ij}$, the energy at node N_j can be estimated by node N_i (whenever it hears a retransmission by node N_j or when it is aware N_j receives a message) as

$$\widehat{E}_{ij}^{(k+1)} = \widehat{E}_{ij}^{(k)} - d_{ij}^{(k)}E_T - (1-d_{ij}^{(k)})E_{IR} \qquad (14)$$

There are, however, messages received by N_j that node N_i is not aware of. Experimental results show that this slight energy overestimation seems to affect neighbor nodes concentrated in a local region in a similar way, so it results not significant to make routing decisions.

F. Q-PR Algorithm

The *Q-PR* algorithm is summarized as follows,

FORWARDING PHASE (N_i receives a message with a list of other candidates)

if Candidate nodes with higher priority forward the message **then**

  N_i discards the message

else

  1. N_i selects the potential forwarding subset ϕ_i^*

2. N_i evaluates $P(T=1|\mathbf{x})$ according to (5) and makes decision d_i whether to transmit or not according to (4)

if $d_i = 1$ **then**

Broadcast the message destined to ϕ_i^*

Broadcast its expected $\widehat{Q}_i(\phi_i^*)$ computed as (11)

Listen to retransmissions and update candidate neighbor profiles according to (13)

if no candidate nodes forward **then**

go to step 1.

end if

end if

end if

INFORMATION UPDATING PHASE

N_i updates $\widehat{Q}_i(j)$ via RL according to (9) from any neighbor N_j that broadcasts its cost metric.

N_i updates $\widehat{E}_{ij}$ according to (14) when it hears a retransmission by N_j or it knows N_j receives a message

4. Simulation results

Experimental results are carried out over a network topology with 100 homogeneous nodes with equal initial energy resources, that have been randomly deployed in a test 10×10 area. Node energy is initialized uniformly and power consumption ratios of idle:receiving:transmission are set to 1:1:2.5. Parameter γ in Eq. (4) was fixed to 1. We assume as neighbor nodes those with delivery probability $\alpha > 0.05$.

Note that loss links are also considered in these simulations according to the model presented in Sect. 3-B with $\beta = 2$ and $R = 2.5$ (a perfect channel knowledge is assumed). Parameters such as μ (adaptive step of the weight vector in (13)), ϵ (explained in Sect. 3-C.1) and η (learning rate to update the Q metric in (9)) are fixed to 0.05, 0.05 and 0.01, respectively, and remain constant with time. We consider unicast transmissions from randomly chosen sensors to the sink node, represented by the rightmost node in the field. Sensors transmit messages with an importance value selected at random as an integer between $I = 1$ and $I = 10$. Our Q-PR algorithm is compared to GPSR (Greedy Perimeter Stateless Routing) [18] [7], a well-known and widely analyzed position-aware routing algorithm in sensor networks and to EFE (Expected progress-Face-Expected progress) [19], which considers a realistic physical layer. Results were averaged over 50 different topologies of connected networks.

A major problem in routing algorithms based on greedy forwarding occurs when the forwarding node has no neighbors closer to the destination than itself. GPSR tries to solve it by means of perimeter forwarding on the planarized network graph using the right-hand rule, just like EFE does. RNG (*Relative Neighborhood Graph*) planarization has been implemented [7]. Q-PR tackles it by means of the aforementioned prioritized list of candidates as a function of the delivery probability. Fig. 2 illustrates this: a route has to be found from N_{14} to the sink (N_{54}). When the message reaches node N_{28} (following the thick line), no neighbors are closer to the sink than itself. However, the message successfully reaches again one of the ways to destination, coming back to node N_{78}.

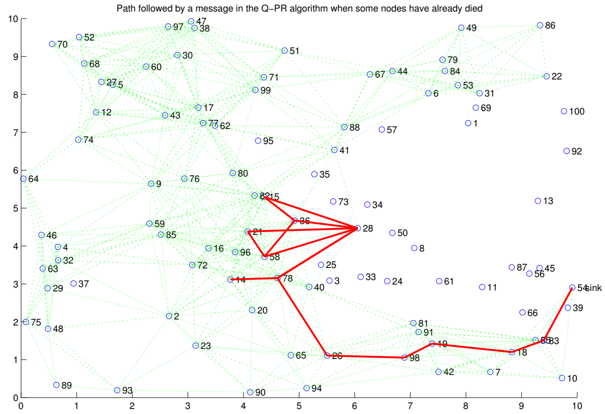


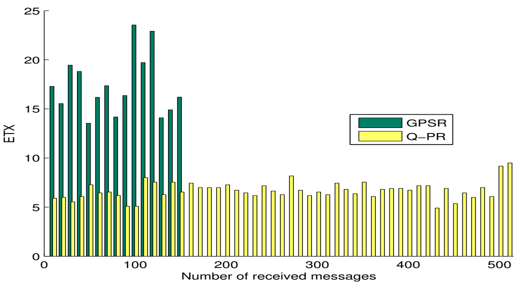
Fig. 2: Illustration of network topology and routing path between node N_{14} and the sink node (node N_{54}). Discontinuous links show neighborhood relationships. Dead nodes have no discontinuous connection lines.

Table 4: Performance assessment and comparison between Q-PR, GPSR and EFE algorithms. (% (mean ± std))

	Successful delivery rate	Received messages	Received average importance	Sum of received import.	RIR
Q-PR	98.12 ± 1.72	584 ± 86	6.05 ± 0.13	3531	0.99
GPSR	75.66 ± 4.29	154 ± 25	5.49 ± 0.21	847	0.76
EFE	98.04 ± 3.10	171 ± 33	5.51 ± 0.21	940	0.99

In order to simulate routing protocols under the same circumstances, we have made GPSR more robust establishing a maximum number (equal to 20) of transmission retries before discarding the message, as considered in [7] for cases of mobile networks. In EFE, the sender node keeps transmitting the packet (up to 20 retries) to the subsequent candidate until the packet is acknowledged successfully. Q-PR performance is assessed in terms of ETX and the metrics shown in Table. 4, where network lifetime is defined by the time slot when there is no route to reach the sink node, and the Received Importance Ratio (RIR) is the ratio between the sum of received importances and the total importance generated by the network traffic.

Results recorded in Table 4 show that Q-PR outperforms GPSR in terms of successful delivery rate (98.12% against 75.66%) but it is similar to EFE (98.04%). Moreover, due to the high number of retransmission retries and acknowledgements (6.08 for Q-PR, 15.82 for GPSR and 10.50 for EFE on average) as well as the high message loss in the case of GPSR, the Q-PR algorithm allows the nodes to keep energy for longer time. Thus, the network lifetime with Q-PR is 751 slot times vs. 203 for GPSR and 174 for EFE. An example of the temporal evolution of ETX to destination is shown in Fig.3. Note that GPSR and EFE allow to transmit to the sink much less than half (26.37% for GPSR and 29.28% for EFE, on average) of the messages Q-PR does (154 and 171 against 584). Note also that, although GPSR allows to reach



(a)

Fig. 3: Temporal evolution of ETX for a single simulation concerning to groups of 10 messages received by destination for the GPSR and Q-PR algorithms.

the destination with lower number of hops than Q-PR and EFE (3.57 against 5.66 and 5.76, respectively; due to the fact that the optimal forwarding node in GPSR is the closest to destination), the number of successfully received messages is much lower than Q-PR.

It is worth noting that not only the number of messages that reach the destination is higher with the Q-PR algorithm but also (i) the sum of the importance (of received messages) and (ii) the ratio between the received message importance and the total message importance generated in the network nodes, compared to GPSR in this last case. In brief, the Q-PR model loses fewer messages and also less important information. Q-PR saves energy in order to forward messages of higher importance and thus contribute to maximize the sum of the importance of the received messages. Thus, a careful analysis of Q-PR performance shows: (a) there are some messages that source nodes decide not to send and (b) the importance average of the non-sent messages in the Q-PR model depends on the γ parameter that defines the transmission decision threshold.

5. Conclusions and further directions

Q-Probabilistic Routing (Q-PR) is an energy-aware routing algorithm for wireless sensor networks which incorporates intelligent routing decisions adapted to the network dynamics by: (1) estimating a global cost metric locally learned through RL rules during neighbor interactions, and (2) taking forwarding decisions by means of a Bayesian decision model.

Experimental results show that Q-PR allows to increase successful message transmissions as well as to keep a trade off between network lifetime and ETX. Moreover, transmission of least important messages is suspended in favor of high priority messages by considering the message importance in routing decisions, what is seldom studied in the literature.

The result analysis reveals that Q-PR could be further improved by means of a dynamical adjustment of parameter γ in Eq. (4) (balancing the message importance with the energy cost), and a refinement in the residual energy estimation at neighbor nodes. Both of them as well as exploring alternative methods to select forwarding nodes that do not require neighborhood requisites are some of the goals for future work.

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