A Bayesian Decision Model for Intelligent Routing in Sensor Networks

Rocío Arroyo-Valles, Antonio G. Marqués, Juan José Vinagre-Díaz and Jesús Cid-Sueiro

***Abstract*—In this paper we propose an efficient energy-aware routing algorithm based on learning patterns. Energy and message importance are considered in a Bayesian model in order to establish intelligent decision rules that make the network economize in crucial resources.**

I. Introduction

Recent advances in sensor technology and wireless communications have enabled the development of dense wireless networks of small, low cost, low-power and multifunctional sensor nodes which communicate in short distances either directly or through other nodes by a wireless medium [1]. Sensor nodes are constrained by resources such as energy consumption (which limits the network lifetime [2]), storage capacity and processing power [3]. Network topology may change and suffer from connectivity failures, and needs to be built and updated in real time.

When deploying sensor nodes, survivability and adaptation to the environment should be assured via redundant paths and efficient routing algorithms [4]. Several diffusion methods, that only use information coming from neighbor nodes, can be used for this purpose [5]. The position of the sensor nodes is not required to be predetermined in advance [1], which makes deployment feasible where there is no infrastructure at all. A considerable number of sensor network routing algorithms require location techniques to know its accurate position to set up the connectivity graph, without needing global knowledge.

Routing is one of the challenging open issues in sensor networks (SN) [3]. According to the forwarding method, they are classified into two groups. In the algorithms which belong to the first group, packets are replicated and sent along all possible neighboring nodes. When a node receives more than a copy, it discards it to reduce power consumption [6]. In selective forwarding, only some nodes keep the responsibility of forwarding the message depending on the conditions. Probabilistic forwarding, included in this group, is chosen to fight against exposed restrictions and to assure reliable routing. Considerable research has been focused on the design of power-aware protocols and efficient algorithms for SN to prolong sensor lifetime [1] [3].

In this paper, we propose an efficient energy-aware routing model based on learning patterns. Sensor nodes learn from past routing decisions depending on the success or failure of their transmissions. Each node observes if neighboring nodes forward their messages in order to improve routing performance in later chances by doing probabilistic routing, as it is also suggested in [7] [8]. The node decisions are based not only on the available energy in nodes but also on the importance of the message to be transmitted. Probabilistic estimation of distributed parameters in the network will reduce the amount of information stored, transmitted and updated trough the network.

The rest of the paper is structured as follows. Section II details our probabilistic decision model and in Section III, simulations with synthetic data are proposed and results are analyzed. Finally, in section IV, the conclusions and future works are exposed.

II. Decision Model

Consider a network of N sensor nodes $\{i; i = 1, \ldots, N\}$. All nodes are assumed to be homogeneous and non hierarchically organized, having similar resources, and all of them are assumed to behave according to the same rules. These nodes are spread along a geographical area, and can send information packets among themselves. Due to power limitations, each node can only transmit messages to nodes inside its coverage area. We will denote $\phi(i)$ as the set of all nodes in the coverage area of node i, so that any message sent by node i will be received by all nodes in $\phi(i)$. Reciprocity between coverage areas is assumed (i.e. if $j \in \phi(i)$ then $i \in \phi(j)$), which is a natural assumption if the nodes have a single antenna. We analyze two different variants: in model 1, we assume that nodes have no idea about its (absolute or relative) geographical location. In model 2, we assume that node i knows its geographical position, $\mathbf{z}_i$, and can find out the geographical coordinates of all its respective neighbors in $\phi(i)$ (eg. [9], [10]).

All messages should be addressed to a special node called sink (a.k.a. access point), whose geographical location is also known by all nodes in model 2 because it is connected to the external structure to further processing, but not in model 1. Without loosing generality, let N be the sink node and $\mathbf{z}_N$ its geographical position. Each time a node generates or receives a message it must make a decision about sending it to other nodes, or not (see Fig. 1).

Determining to how many nodes a certain message is delivered is an important issue. In order to avoid spreading messages in the opposite direction, node i in model 2 first checks if the message is being forwarded in the adequate direction, even if a higher delay is incurred. If node i has received the message from node j and $\|\mathbf{z}_i - \mathbf{z}_N\| > \|\mathbf{z}_j - \mathbf{z}_N\|$, the message will not be forwarded by node i. On the contrary, if node $\|\mathbf{z}_i - \mathbf{z}_N\| \leq \|\mathbf{z}_j - \mathbf{z}_N\|$, node i proceeds to analyze the state of all neighbors that are closer to the sink than itself.

1-4244-0398-7/06/$20.00 ©2006 IEEE

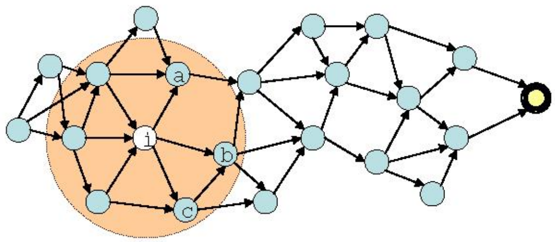

Fig. 1. A network of sensor nodes. The shaded circle shows the coverage area of node i (if no obstacles are considered and sensor antennas are omnidirectional the coverage area of i will be represented by a circle whose center is the node i). All nodes inside the circle (unless i) is the set of neighbors, $\phi(i)$. Each time node i receives a message, it should make a decision about forwarding it to other nodes or not. To do so, it analyzes the state of all neighbors that are closer to the sink (the right double circle in the figure), namely, nodes a, b and c.

We will denote $\phi_+(i)$ as the set of all nodes in $\phi(i)$ whose distance to node N is smaller than $\|\mathbf{z}_i - \mathbf{z}_N\|$.

Decisions at node i will be based on the following variables:

- An estimation of the available energy at neighboring nodes, $\{\hat{E}_{ij}, j \in \phi_+(i)\}$.
- The importance of the message to be transmitted, I. The evaluation of the importance of a message is a responsibility of the source node (different importance values are selected when going beyond different thresholds), and it should be transmitted along with the message.

Since nodes in model 1 do not know which of their respective neighbors are closer to the sink, the decisions at node i in this model will be based on the energy estimation at any of the neighboring nodes.

Assuming that most energy consumption is caused by transmissions, the estimation

$$\hat{E}_{ij}(k+1) = \hat{E}_{ij}(k) - n_j(k)E_T \tag{1}$$

where n_j is the number of messages transmitted by node j at time k and E_T is the energy consumed per transmission. Note that our model assumes that the energy consumptions are the same at each transmission (which is a reasonable approximation if information is sent in packets of equal size), and that node i 'listens' all transmissions done by its neighbor, j.

All these variables are grouped into observation vector $\mathbf{x}$. Each node with a message to transmit states the decision as a result of solving a hypothesis testing problem with two hypothesis, $T = 0$ or $T = 1$, where:

- $T = 1$ if at least one neighbor will forward the message.
- $T = 0$ if no neighbor will forward the message

Depending on its belief about the value of T, node i will make decision $\mathcal{D}_1$ (the message is transmitted) or $\mathcal{D}_0$ (the message is not transmitted).

To do so, we define cost $C(\mathcal{D}_i, d) = c_{id}$ as the cost of deciding D_i when the true hypothesis is $T = d$ (where $i, d \in \{0, 1\}$) so that: $c_{00} = 0$, $c_{10} = E_T$, $c_{01} = 0$ and $c_{11} = E_T - I$. The importance of the messages contributes to the reduction of the cost only if the message is forwarded by some of the neighboring nodes. According to this, the mean cost of deciding D_0 and D_1 become

$$\begin{aligned} C(\mathcal{D}_0|\mathbf{x}) &= 0 \\ C(\mathcal{D}_1|\mathbf{x}) &= E_T - IPr\{T = 1|\mathbf{x}\} \end{aligned} \tag{2}$$

so that the final decision is given by D_1 if $Pr\{T = 1|\mathbf{x}\} > \frac{E_T}{I}$ and D_0 otherwise.

In order to estimate the posterior probability of each hypothesis, node i makes two simplifying assumptions:

a1) The probability of node j forwarding a message is independent of the forward decision made by any other nodes.

a2) The probability of node j forwarding a message is independent on the state of any other nodes.

As a consequence of a1), and defining the random variable T_j equal to 1 if node j will forward the message and 0 otherwise, we can write

$$y_{ij} = Pr\{T = 1|\mathbf{x}\} = 1 - \prod_{j=1}^{L}(1 - Pr\{T_j = 1|\mathbf{x}\}) \tag{3}$$

As a consequence of a2), we have $Pr\{T_j = 1|\mathbf{x}\} = Pr\{T_j = 1|\mathbf{x}_j\}$ where $\mathbf{x}_j = (\hat{E}_{ij} \quad I \quad 1)^T$. Note that the last component (equal to unity) has been included for mathematical convenience.

We assume a truncated logistic model

$$y_{ij} = Pr\{T_j = 1|\mathbf{x}_j\} = \frac{1}{1 + \exp\left(-\mathbf{w}_j^T \mathbf{x}_j\right)} u(\hat{E}_{ij} - E_T) \tag{4}$$

where u is the Heaviside step function. Note that node i assigns a zero probability of retransmission to any node that (according to its estimates) does not have energy for transmitting the message.

The probabilistic dependencies which define the decision process at each node are illustrated in Fig. 2. Each transmitting node "builds" a graphical model including the most relevant variables in the node decision: namely, the importance of the message and the energy of the neighboring nodes. Though each node makes the simplifying assumption that the neighbor decision will not depend on the energy at other nodes, it tries to learn some probabilistic dependencies through the logistic model.

Notice that according to the forwarding method, our work can be classified into both groups of algorithms discussed in Section I. We use probabilistic forwarding to select nodes but we do not choose a unique path. We also make use of packet replication to guarantee that the termination node receives the message.

A. Learning

When node i sends an information packet, it keeps 'listening' the channel. Due to the reciprocity between the coverage areas of neighboring nodes, if an element of $\phi(i)$ forwards the message, node i can detect the retransmission, and use this feedback information to update its profile of the neighboring

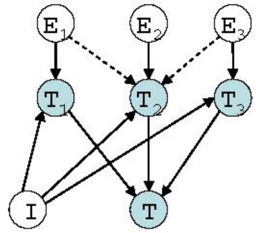

Fig. 2. The graphical model build by a transmitting node including the importance of the message and the energy of the neighboring nodes. Each node makes the simplifying assumption that the neighbor decision will not depend on the energy at other nodes (thus omitting dependencies given by the dashed arrows, that could appear if node neighbors are neighbors themselves.

nodes. Let d_j a binary variable equal to 1 if node j forwards a message received from i (or, more precisely, if node i listens node j forwarding its message) and 0 otherwise. Parameters $\mathbf{w}_j$ are estimated in order to minimize cross entropy loss function [11] given by

$$L(y_{ij}, d_j) = -d_j \ln y_{ij} - (1 - d_j) \ln(1 - y_{ij}) \qquad (5)$$

For computational simplicity, we use stochastic gradient learning rules, so that, after transmitting any message, node i updates all parameters as

$$\mathbf{w}_j(k+1) = \mathbf{w}_j(k) + \mu(d_j(k) - y_{ij}(k))u(\hat{E}_{ij} - E_T)\mathbf{x}(k) \quad (6)$$

It is important to emphasize that sensor nodes do not need to exchange any specific information among nodes to carry out the learning phase, since they just use the information associated to forwarded transmissions. Proceeding in this way we enable a total decentralized routing design which at the same time takes into account non-local information.

III. Experiments with synthetic data

We have carried out an extensive number of experiments with the routing algorithm presented in this paper. Simulations have been implemented in order to evaluate the proposed algorithm performance and to analyze the influence of the different design variables taken into account. Since our model tries to represent a real sensor network, several nodes have been deployed in a test scenario to reflect a realistic system. Furthermore, it is noteworthy that the implemented model only focuses on the routing algorithm and does not go into details of the underlying layers. Additional constraints due to nodes connectivity are not considered to simplify the model and analyze results independently. Nevertheless, network topology may present obstacles that limit the nodes connectivity apart from the restrictions imposed by the propagation.

A communication session starts when a node needs to transmit a message with relevant information to the sink in model 2 or to all the nodes in model 1.

In addition, as a result of the broadcast nature of the wireless channels, neighboring nodes of the sender node receive messages to be forwarded to the sink, even if they are placed in a path that moves further away from it. In this case, they will not forward the message as a way of saving energy.

In our simulation example, 100 homogeneous nodes of equal capabilities (equal initial values of energy) have been randomly deployed in a test 10×10 m^2 area (the choice of a square field is made in order to simplify the experiments). Sensor nodes deployment associated to one of the simulation runs is showed in the network topology of Fig. 3. Origin nodes are randomly chosen whereas the sink is the right most node in the field. Position information is also taken into account when implementing model 2. Considering a random importance for each generated message, we compute in which transmission the network 'dies' due to absent of energy (scenario 1). After calculating the average importance value of the transmitted messages, we simulate scenario 2, where all the messages have the same importance value.

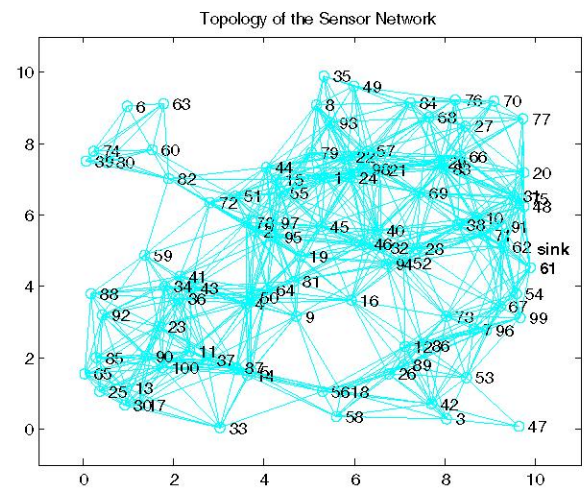

Fig. 3. Network topology associated to one of the simulation runs, where sensor nodes are deployed in a 10×10 m^2 field

Parameters such as μ (the adaptive step of the weight vector in (6)), the maximum distance to consider a sensor node as a neighbor and the consumed energy performing a transmission have been set from preliminary simulations and remain constant during all the simulation process.The results presented here were averaged over 10 simulations runs.

We compare our proposed Bayesian routing model (both versions, the location-aware routing algorithm and the intelligent routing model without location knowledge) to the flooding algorithm. We chose the flooding model because its simplicity and as far as we know, there is no other model that considers the importance value of a message to minimize the energy consumption.

The parameters under study are the different levels of the importance of the generated messages and the last transmission that produces the network's death (none of the nodes receives the transmitted message). Fig. 4 shows the evolution of the last transmission value when the importance of the messages is not the same considering the location-aware routing model.

We can see from the curves corresponding to the first scenario that when the value of the importance is low, some messages are not sent and consequently the last transmission

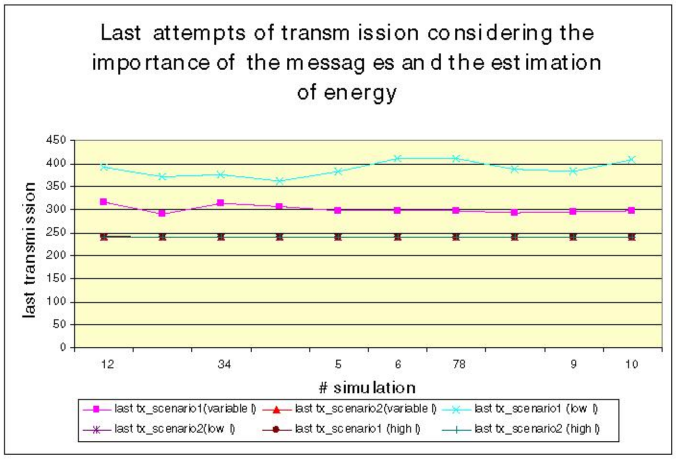

Fig. 4. Evolution of the last transmissions carried out in the sensor network considering different values of the importance of the messages in the location-aware routing algorithm

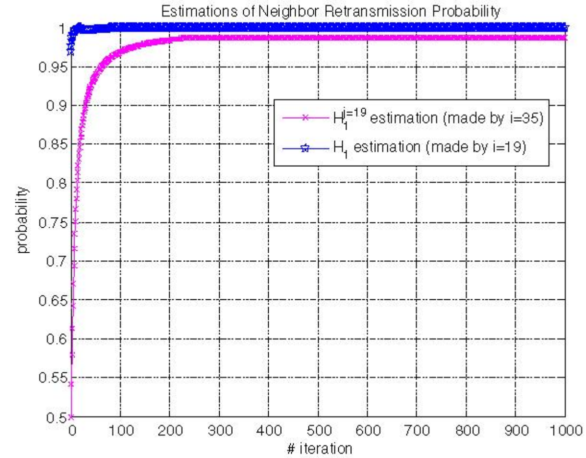

Fig. 5. Example showing the expectations of collaboration that a neighboring node (19) retransmits the message generated by node 35. It also shows the expectations that some neighboring node of 35 retransmit the message

is produced later than in the second scenario. This is due to the decision criterium and the learning techniques of the nodes. This implies that sensor network lifetime is increased and batteries in sensor nodes last longer. In high importance messages, the last transmission value is practically the same (both networks try to send all messages avoiding discarding messages of high importance). When the importance varies from 1 to 10, an intermediate situation is reached given that low importance packets may not be forwarded in favor of sending top priority messages. Table I reflects the extracted conclusions from Fig. 4 calculating the average value of the importance and the last transmissions.

TABLE I

LAST PRODUCED TRANSMISSION FOR DIFFERENT LEVELS OF IMPORTANCE (AVERAGED OVER 10 RUNS) CORRESPONDING TO THE LOCATION-AWARE MODEL

I	Average I	last tx scenario 1	last tx scenario 2
low (0-5)	3.01131	388.7	239.7
variable (0-10)	5.5059	300.7	240.5
high (5-10)	7.4720	241.1	240.9

The analysis is complemented with Fig. 5. As example, we show the expected forwarding probability (i.e. a neighboring node retransmits a message generated in an origin node). We also represent the expectations that some neighbors also retransmit the message. Notice that both curves tend to converge since the importance of each generated packet remains constant when transmitting through the network (nodes are not allow to modify the importance of the messages originated at other nodes) and the transmission energy is constant, too. The more the neighboring nodes retransmit the messages, the more reliance get the nodes connected to it. Depending of the selected μ value, the convergence speed varies.

Varying the importance of the messages Fig. 6 shows the evolution of the last produced transmission in a flooding routing model, and Table II summarizes the obtained results. As the importance is not considered when routing, all packets are handled in the same way so that the network time life is approximately the same.

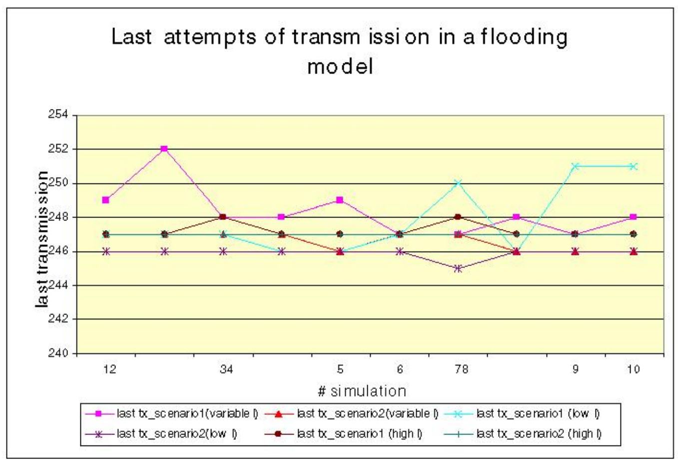

Fig. 6. Evolution of the last transmissions carried out in the sensor network considering different values of the importance of the messages in the flooding routing algorithm

Comparing both routing algorithms, our intelligent model outperforms the flooding algorithm since the last transmission is produced later. This effect is clearly observed when low importance packets are transmitted. These are expected results since our routing algorithm saves energy sending messages to nodes with high probability of forwarding them towards the sink, according to the available energy and the importance level of the messages. However, in the flooding algorithm all messages are sent to all possible nodes, without any special consideration, and consequently power resources are faster used up.

When comparing two models of the selective routing model (see Table III for model 1), there are not excessive differences

TABLE II

LAST PRODUCED TRANSMISSION FOR DIFFERENT LEVELS OF IMPORTANCE (AVERAGED OVER 10 RUNS) CORRESPONDING TO THE FLOODING MODEL

I	Average I	last tx scenario 1	last tx scenario 2
low (0-5)	2.95024	247.8	245.9
variable (0-10)	5.5711	248.3	246.6
high (5-10)	7.5463	247.2	247

related to the previous explained results. The main difference is that in the location aware algorithm, sensor nodes know their geographical positions and they may exclude those nodes that do not progress the message in the right direction towards the sink. In this way, energy remains longer at nodes and it can be used for other transmissions. This is a reason for having a slight better performance compared to the model without location knowledge, and reducts the system overhead. Instead, we have to provide sensor nodes with the capability of discovering its actual position.

TABLE III

LAST PRODUCED TRANSMISSION FOR DIFFERENT LEVELS OF IMPORTANCE (AVERAGED OVER 10 RUNS) CORRESPONDING TO THE INTELLIGENT MODEL WITHOUT LOCATION KNOWLEDGE

I	Average I	last tx scenario 1	last tx scenario 2
low (0-5)	3.02602	387.6	239.9
variable (0-10)	5.5192	297	240.6
high (5-10)	7.53181	240.9	240.8

IV. CONCLUSIONS AND FUTURE WORK

In this paper, we presented a new efficient energy-aware routing algorithm based on learning patterns for SN that minimizes the main constraints imposed by this kind of networks. Our probabilistic decision model both considered the estimation of the available energy at the neighboring nodes and the importance of the messages to make intelligent decisions. The idea came from the fact that if the estimation of the available energy and the importance of the messages are high, the reliability is increased and nodes trend to forward messages. In order to achieve these objectives, it was necessary to apply the ideas exposed in the paper in a test scenario. We studied its behavior carrying out a set of experiments, proposing two different variants of the intelligent routing algorithm: a location-aware scenario and another having no idea about this information. We both compared to the flooding algorithm and our routing algorithms had clearly better performance making the network last longer saving energy used to transmit messages, specially if they have high importance. The success in the results of the proposed Bayesian model means being considered as an alternative to other existing routing protocols.

After these initial results, some open questions are left to explore in a future work. A more general model can be accomplished, where energy consumption is not only due to transmissions. Reception, idle modes and active mode (without transmitting) should not be rejected both in the formulation and in the evaluation. A variable energy of transmission can also be considered since energy consumption depends on the distance between communicating nodes. In addition, a lossy model can be studied. Link loss is another parameter whose effect can be reflected in the network performance since not all the nodes are the most appropriate to have a reliable transmission, thus some nodes can be excluded of being selected as a next hop in transmissions. We can also extend the proposed model to mobile SN, making our routing protocol appropriate for another application scenarios. The effects of spreading more sensor nodes after doing the first deployment to prolong sensor lifetime or adding new sinks can be some other modifications for the purposes of study. The overhead of the scheme can be discussed too. The location aware routing protocol is quite close to the GPSR protocol in the sense that both exploit the correspondence between geographic position and connectivity by using the positions of nodes to make packet forwarding decisions [12]. A way of enlarge this work can be comparing these two models.

ACKNOWLEDGMENT

This paper has been partially supported by MEC projects TEC2005-06766-C03-01/TCM and TEC2005-06766-C03-02/TCM, CAM-UC3M projects RECIPES (UC3M-TEC-05-058) and UC3M-TEC-05-059, and EHAS Project from the ALIS Program, financed by the European Union.

REFERENCES

[1] I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Communications Magazine*, vol. 40, no. 8, pp. 102–114, 2002.

[2] "Sensor networks: An overview," http://wwwcsif.cs.ucdavis.edu/ bharathi/ sensor/survey.pdf, 2001.

[3] Q. Jiang and D. Manivannan, "Routing protocols for sensor networks," *Procs. of the IEEE (CCNC)*, pp. 93–98, 2004.

[4] F. Stann and J. Heidemann, "Bard: Bayesian-assisted resource discovery in sensor networks," *INFOCOM 2005. 24th Annual Joint Conference of the IEEE Computer and Communication Societies. Proceedings of the IEEE*, vol. 2, pp. 866–877, 2005.

[5] C. Chong and S. Kumar, "Sensor networks: Evolution, opportunities, and challenges," *Procs. of the IEEE*, vol. 91, no. 8, pp. 1247–1256, 2003.

[6] J. Wu, L. Chen, P. Yang, J. Zhou, and H. Jiang, "A new reliable routing method based on probabilistic forwarding in wireless sensor network," *Procs. The Fifth International Conference on Computer and Information Technology*, vol. 7, no. 5, pp. 524–529, 2005.

[7] A.Lindgren, A. Doria, and O. Schelen, "Probabilistic routing in intermittently connected networks," 2003.

[8] A.A.Papadopoulos, J. McCann, and A. Navarra, "Connectionless probabilistic (cop) routing: an efficient protocol for mobile wireless ad-hoc sensor networks," *Performance, Computing, and Communications Conference. IPCCC 2005*, pp. 73–77, 2005.

[9] D. Niculescu and B. Nath, "Ad hoc positioning system (aps)," *Procs. of the IEEE Global Telecommunications Conference (GLOBECOM)*, vol. 5, pp. 2926–2931, 2001.

[10] N. Bulusu, J. Heidemann, and D. Estrin, "Gps-less-low-cost outdoor localization for very small devices," *IEEE Personal Communications (see also IEEE Wireless Comms.)*, vol. 7, no. 5, pp. 28–34, 2000.

[11] J. W. Miller, R. Goodman, and P. Smyth, "On loss functions which minimii to conditional expected values and posterior probabilities," *IEEE Trans. on Information Theory*, vol. 39, no. 4, pp. 1404–1408, 1993.

[12] B. N. Karp, "Geographic routing for wireless networks," *PhD. Thesis*, 2000.