An Adaptive Epidemic Information Dissemination Scheme with Cross-layer Enhancements

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Abstract—**Ad hoc networks such as Wireless Sensor Networks (WSN) are characterized by the scarcity of energy resources (among other resource types). Their intelligent design can extend their lifetime without compromising the operation of network nodes and the applications running on them. To this end we propose an adaptive epidemic scheme that helps reduce energy expenditure through intelligent tuning of the infection (forwarding) rate. Redundant communications and experienced error rate drive the adaptation of the forwarding rate. Simulation results show that significant energy gains can be obtained through the proposed scheme.**

***Index Terms*—Ad hoc networks, Wireless sensor networks**

I. Introduction

Wireless sensor networks consist of nodes with minimal resources in terms of transmission, computing power, bandwidth and storage. It is a common requirement that the information owned by them has to be shared by other nodes and in many cases (e.g., monitoring applications in a WSN) it has to be delivered to as many nodes as possible. This can be achieved through established information dissemination schemes.

The adoption of epidemic information dissemination models means transmitting in a probabilistic rather than deterministic manner [8], [13]. This leads to curtail redundant communication. Less energy and network resources are, thus, spent in the attempt to disseminate information to a large percentage of network nodes [6].

Unconditional data flooding by all nodes to all their neighbors can only partially tackle the problem as it results to excessive resource consumption [17], [18].

We adopt the epidemic paradigm for information dissemination within the WSN and propose an extension scheme, in which the forwarding probability is dynamically tuned taking into account (i) the amount of the redundant message exchanges and (ii) the error rate due to channel noise observed on each node. The aim of the extension scheme is the reduction of redundant, unnecessary transmissions, while the forwarding rate can be increased at the presence of noise, in order to secure a more efficient communication. The bottom line is to achieve efficient information dissemination at a lower energy cost, thus, rationalizing resource use.

The structure of the paper is as follows: In section II some important concepts in epidemic dissemination are laid out and the rationale of our proposal is introduced. In section III some significant previous work on the issue of adaptive epidemic schemes is presented. Section IV is dedicated to the detailed analysis of our system model. Models for the network and the wireless channel are also elaborated upon in this section. Additionally, the suggested adaptive epidemic model is presented in detail. Section V concerns some useful metrics for evaluating the model as well as simulation results. Finally, some conclusions together with future work prospects are presented in section VI.

II. Rationale

Epidemic-based information dissemination is a well known model for disseminating information in ad hoc wireless networks [1]. It guarantees the reception of pieces of information by as many network nodes as possible by "infecting" them in a probabilistic rather than deterministic manner. This occurs at a given forwarding probability $\beta \in [0, 1]$ (a.k.a. infection rate). The probabilistic nature of the epidemic scheme reduces redundant transmissions [6]. An infected node can 'infect' other neighboring nodes, but that node can be cured too. Nodes that do not carry the infecting information are assumed to be in the *susceptible* state, whereas those that do are in the *infected* state. The cure of an infected node can occur at some time once the infecting piece of information turns unusable-obsolete. This can occur at a cure rate $\delta \in [0, 1]$.

The forwarding probability, β is the key parameter that we adjust in our scheme, in order to improve the information dissemination efficiency. The efficiency in information dissemination for a certain model is defined as the percentage of nodes that have received information out of the total number of message exchanges per unit time. This is detailed in section V together with other metrics used in our evaluation.

Two well-established and known epidemic models concerning the above behavior are the Susceptible-Infected-Susceptible (SIS) and the Susceptible-Infected-Recovered (SIR) models [1]. In the SIR model, a cured node cannot be re-infected later, thus, becoming immune (or recovered (R), removed). On the other hand, in the SIS model, a node is in either the susceptible (S) or the infected (I) state before or after an infection, respectively.

The infection process in an epidemic model includes communication and processing of the infecting information on behalf of the nodes. This incurs an energy consumption burden. Minimizing this, while still efficiently infecting the maximum possible proportion of nodes is the objective of our adaptive scheme. In the proposed scheme, the volume of corrupted and duplicate messages received are monitored on each node. Hence, the forwarding probability (β) for each node is locally adjusted depending on such specific measurements. That is, the β rate:

- increases with the error rate (ratio of corrupted messages over total received message count); a high error rate is attributed to the channel conditions. Increasing the forwarding rate ensures that an adequate amount of infecting information shall be correctly received and, thus, infect a large proportion of the WSN nodes.
- decreases with the duplicates rate (ratio of received duplicate messages over total received message count). An increased rate of duplicates means that it is very likely that a node is already infected when an infecting packet is received. Therefore, this second reception is unnecessary and omitting would be advisable. Reducing the forwarding rate effectively means that we may reduce the duplicates without reducing the number of nodes infected.

III. Previous Work

Redundant transmissions due to the multipath propagation associated with ad hoc WSNs, where nodes do not have global topology knowledge, are a significant energy-consumption factor. Various approaches to overcome this issue have been proposed. It has long been suggested that nodes apply selective forwarding schemes depending on local conditions. In [7] an active scheme is suggested, according to which nodes are explicitly queried about their residual energy and their neighbors adjust their forwarding rate accordingly. Other approaches specify target node selection before information forwarding is attempted; in general a subset of a node's neighbors is selected as target nodes. The selection process is based on local information. In [9] an adaptive forwarding rate is proposed, using the measured error rate in the wireless channel as input. In [10], on the other hand, a publish-subscribe paradigm is assumed, which can assist in filtering some nodes out of the potential disseminated information receivers. One notices, that, whereas the former is an essentially passive method, the latter has the features of an active one as an active publish-subscribe scheme is a prerequisite.

Further passive methods like utilizing a time-to-live field in the disseminated information may also bring improvement as well as artificially limiting the buffer size [11]. However, a trade-off needs to be defined here, as non-redundant traffic may be affected too. An interesting approach proposed in [12] foresees quench waves, consisting of messages of a protocol whose specific purpose is to limit redundant transmissions at nodes that receive them. This active method can contribute to flooding rather than restrict it, if the quench wave is sent at a late stage. The model in [13] is based on a node adapting its own forwarding rate based on local network density awareness. According to this model, over-frequent transmissions are unnecessary in a dense network.

We contribute to the field of adaptive epidemic schemes by suggesting a scheme which is passive, as it is based on local decisions and does not incur any extra communication energy cost. Neighboring nodes are not polled on their residual energy or their infection state. Forwarding towards neighboring nodes is determined probabilistically. This probability is incremented in case of high channel noise to counterbalance high losses, and decremented in the opposite case in order to minimize redundant transmissions. Additionally, it contains a component of cross-layer awareness builds on innovative previous work [3] in this field. It offers adaptability in terms of error correction coding and modulation scheme and performs well with a correspondingly changing overhead size.

IV. System Model

A. Network Model

We assume a WSN with N potentially mobile nodes. Any infected node is a source of the infecting information, whereas any susceptible node is a potential consumer. At the beginning, a finite number of nodes are infected; this setting matches with the case of sensor-enabled nodes which disseminate the information they possess. The mobility model for the nodes is the Random Way Point model [18]. Each node is indexed with an integer value. The neighborhood of a node i at time t is denoted by the set $V_i(t)$ and a node j is neighbor to node i at t if $j \in V_i(t)$ node j is within the communication range of node i. At time instance t, let $I(t)$ and $S(t)$ be the set of nodes being in the infected and the susceptible state, with $|I(t)|+|S(t)| = N$. $|U|$ denotes the cardinality of the U set.

One has to keep in mind that channel noise renders some infection attempts unsuccessful. Hence the effective rate at which a node infects others should be placed at a value lower than β.

All infected nodes at $t = 0$ initialize the infection rate $\beta_i(0)$ with the same value β_0, for all $i \in I(0)$. Each infected node i adjusts its infection rate $\beta_i(t)$ at time t. That is it disseminates information to a neighboring node $j\in V_i(t)$ at time t with probability $\beta_i(t)$. Moreover, for an infected node there exists a probability that the conveyed information expires and that node transits anew to the susceptible state. This event occurs to a node i with probability, which is the cure rate δ_i. In our scheme, we assume δ to be equal to a fixed fraction of the current forwarding probability, i.e., $\delta_i(t)=\mu\beta_i(t)$ with $0 < \mu < 1$.

Some useful notation is presented in TABLE I.

B. Channel Model

The wireless channel is assumed noisy, resulting in a finite packet error rate (PER) in the communication between any two neighboring nodes. The noise power experienced at node i at time t follows a Gaussian distribution centered around a known value n_0, which is common for all nodes sharing the same wireless channel [20]. The transmission signal is also assumed common and of constant power, resulting in a finite signal-to-noise ratio γ and PER.

To alleviate the effects of communication over a noisy channel, convolutional error correction coding is utilized. Each node is able to choose for its transmission among different coding schemes corresponding to different coding rates.

We adopt the adaptive modulation and coding model discussed in [3]; each node is capable of transmitting in any mode from a predefined set of coding modes characterized by different modulation schemes and convolutional coding rates. Switching between coding modes occur when predefined SNR thresholds are crossed. Values of specific parameters that assist in the calculation of the PER are also provided in the same work. Such information is consolidated in TABLE II, which is also adopted from [3].

TABLE I
MODEL PARAMETERS

N	NUMBER OF WSN NODES IN THE NETWORK
$I(t)$	Set of infected nodes at time t
$S(t)$	Set of susceptible nodes at time t
$\beta_i(t)$	Forwarding probability at node i at time t. Refers to any node when subscript omitted.
n_0	Mean (Gaussian) noise power
$V_i(t)$	Set of neighbours of node i at time t
$a_i(t)$	State of node i. $a_i(t) = 1$ if and only if node i is infected at time t; $a_i(t) = 0$ otherwise.
$R_{c,i}(t)$	Coding rate of node I at time t
$PER_i(t)$	Packet error rate at node i and time t
$\gamma_i(t)$	Signal-to-noise ratio at node i and time t
$M_i(t)$	Received information over time period [t-w, t) from node i: $M_i(t) = \{m_i(t-w), m_i(t-w+1), \ldots, m_i(t)\}$
$P_i(t)$	Transmitted information over time period [t-w, t) from node i: $P_i(t) = \{p_i(t-w), p_i(t-w+1), \ldots, p_i(t)\}$ It holds that: $p_i(t) = \begin{cases} 1, \text{if if a packet is sent} \\ 0, \text{if nothing is sent} \end{cases}$
$e_i(t)$	Cumulative number of corrupt packets received at node i at time t. Refers to any node when subscript omitted.
$d_i(t)$	Cumulative number of duplicate packets received at node i at time t. Refers to any node when subscript omitted.
$E(t)$	Energy spent till time t with an adaptive β scheme
$E_0(t)$	Energy spent till time t with a static β scheme
n	number of nodes infected over number of transmissions
TXi	Subset of time instances in which node i transmitted: $TX_i=\{t\in\{1,\ldots, T\}\mid p_i(t)=1\}$
RXi	Subset of time instances in which node i received: $TX_i=\{t\in\{1,\ldots, T\}\mid m_i(t)\neq 0\}$
k	Size of the infecting packet in bits

Adopting convolutional error correction coding and choosing to transmit at different coding rate incurs an overhead of varying length to the transmitted infecting data, as will be shown later.

TABLE II
TRANSMISSION MODES IN TM2 WITH CONVOLUTIONALLY CODED MODULATION, FROM [3]

	MODE 1	MODE 2	MODE 3	MODE 4	MODE 5	MODE 6
Modulation	BPSK	QPSK	QPSK	16-QAM	16-QAM	64-QAM
Coding Rate R_c	1/2	1/2	3/4	9/16	3/4	3/4
Rate(bits/sym)	0.50	1.00	1.50	2.25	3.00	4.50
α_n	274.7229	90.2514	67.6181	50.1222	53.3987	35.3508
g_n	7.9932	3.4998	1.6883	0.6644	0.3756	0.0900
γ_p(dB)	-1.5331	1.0942	3.9722	7.7021	10.2488	15.9784

As suggested in [3], we also adopt that the PER is derived from the signal-to-noise ratio according to equation (1).

$$PER(\gamma) = \begin{cases} 1, \text{if } 0 < \gamma < \gamma_{pn} \\ a_n \exp(-g_n \gamma), \text{if } \gamma \geq \gamma_{pn} \end{cases} \quad (1)$$

where the α_n, γ_{pn} and g_n parameters are obtained from TABLE II

C. Proposed Adaptive Scheme

The information dissemination takes place over a noisy wireless channel. This results in both duplicates reception due to the multipath propagation and errors due to the channel noise. We elaborate on this:

Consider an infected node i and a susceptible neighbor node $j \in V_i(t)$ at time t. The successful reception of a piece of data by the node j forces the status of node j to change from the susceptible to the infected state. When a packet is received by a node - besides successful infection - two possible unfavorable scenarios can be thought of:

Case 1: If, due to channel noise, the information is received corrupted at node j, the infection fails and an error is recorded.

Case 2: Due to the multipath and multihop nature of the infecting data propagation, it is possible that the node j receive infecting information from multiple neighbors. Duplicates are received from nodes in its vicinity at that time, i.e. $V_j(t)$. This means that, node j may receive information from node i while already infected. In this case, the information received is considered duplicate and is discarded as redundant.

Duplicates do not contribute to the information dissemination process, but yield an unwanted increase in the energy cost. Moreover, the errors mean that some of the transmissions do not actually assist the actual information dissemination process, either. In our scheme, the β value for an infected node is tuned according to the ratios of duplicate and corrupt over total packets count received by that node.

For every time instant we define a finite history window, $T(w) = [t-w, t)$, $w > 0$. We formalize the received information by a node j over this period as a vector of length w so that:

$$M_j(t) = \{m_j(t-w), m_j(t-w+1), \ldots, m_j(t)\} \quad (2)$$

where $m_j(t)$ assumes the values:

$$m(t)\begin{cases} = m_0, \text{if if the packet is not corrupted} \\ \neq m_0, \text{if the packet is corrupted or not received} \end{cases} \quad (3)$$

where ψ_1 and ψ_2 are arbitrarily defined real numbers.

Then the duplicates rate $d_i(t)$ and the error rate $e_i(t)$ are calculated over this interval $T(w)$ as shown in (4) and (5).

$$d_i(t) = \left|\{\exists l \leq w : m_j(t) = m_j(t-l) = m_0 \mid j \in V_i(t)\}\right| \quad (4)$$

$$e_i(t) = \left|\{m_j(t) \neq m_0 \mid j \in V_i(t), l \leq w\}\right| \quad (5)$$

where w is the width of the time window, i.e., $T(w) = [t-w, t)$, $w > 0$. We investigate two adaptation rules for determining the $\beta(t+1)$ value at time $t+1$ based on the values of the $d(t)$ and $e(t)$ values at time t. These are given in equations (6) and (7).

$$\beta(t+1) = \beta_0(1 - \kappa_1 d_i(t) + \kappa_2 e_i(t)) \quad (6)$$

$$\beta(t+1) = \frac{\beta_0}{1 + \kappa_3 e^{1-\kappa_1 d_i(t) + \kappa_2 e_i(t)}} \quad (7)$$

where κ_1, κ_2 and κ_3 are constant parameters. These are tuned to mitigate the effect of channel losses and multipath propagation and also that the calculated β values remain positive. Hence, we adopt the value ranges presented in Table III.

TABLE III: PARAMETERS FOR THE B CALCULATION

PARAMETER	VALUE RANGE
κ_1, κ_2	0.5 -1.5
κ_3	1.0 – 10.0

With this adaptive scheme, we aim to regulate information forwarding in the presence of too many duplicates and increase them in noisy, error-prone conditions.

We adopt convolutional coding for error correction. The code in use is specified by its coding rate.

In a noisy environment, as quantified by the PER, modulation and coding mode changes and the coding rate is modified accordingly toward lower values, since the SNR thresholds are crossed. These are mentioned in section IV.B as adopted from [3]. The various modes are presented in TABLE II. This modification constitutes an additional variation of the transmission characteristics and changing the amount of the node's energy spent at every transmission.

An infected node at time t observes the values of $d_i(t)$ and $e_i(t)$ of duplicates and corrupt packets respectively within a finite history time interval, i.e., $T(w) = [t-w, t)$, $w > 0$.

D. Infection mechanism of a node

The proposed algorithm is presented in Listing 1. An increase in the $e_i(t)$ rate results to an increase in the β rate and a decrease of the coding rate –inserting more coding bits in the transmitted information- so as to overcome the impact of a noisy channel. This occurs when the SNR thresholds are crossed and transmission assumes a different modulation and encoding mode. The opposite is the case of error rate decrease. Furthermore, an observed large value of duplicates implies a high degree of redundancy which is tackled through the decrease of forwarding probability in a fashion opposite to the previous. According to this epidemic model, the following conditions must be fulfilled, in order for an infection to be successful:

- The target node is a neighbor of the infecting node, i.e. $n_j \in V_i(t)$.
- The infected node "decides" to infect, i.e. a successful random experiment with success probability $\beta_i(t)$, i.e. $m_j(t) \neq 0$.
- The received data is error-free, otherwise the received packet is classified as corrupted and discarded, i.e. $m_j(t) \neq \psi_1$
- The target node is susceptible, otherwise the received packet is classified as a duplicate, i.e. $m_j(t) = \psi_1$

V. METRICS AND EVALUATION

We compare the performance of this scheme with a simple static epidemic one's, where forwarding probability is kept constant.

We define as efficiency of the scheme the ratio of the coverage rate over the number of transmissions (equation 8)

$$\alpha = \frac{n(T)}{M(t)} \tag{8}$$

where $n(t)$ is the coverage rate ratio and $M(t)$ is the cumulative count of nodes infected at time t.

Moreover, the cost gain is defined as the value:

$$h(t) = \frac{E_0(t) - E(t)}{E_0(t)} \tag{9}$$

where $E_0(t)$ and $E(t)$ are the energy costs in the static case and when the adaptive model is used, respectively. This expresses the improvement we obtain through the adaptive model.

```
For t=0:T
   For i∈I              // For every infected node i
      For j∈G-{i}// For all other nodes j
         If αi(t)=1 Then // if node i is infected
            If j∈Vi(t) Then // if node j is neighbor
               If i decides to transmit Then
                  If j receives non-corrupt pkt Then
                     If αj(t)=1 Then // target alr. infd
                        dj(t)++  // incr. dupl. countr
                     End
                  Else ej(t)++
                  End
               End
            End
         End
      End
      βi(t+1) = βi (βi(t) , errorsi(t), dupli(t))//Calc new βi
      Select Rci(t+1)// select new coding rate.
   End
   B = B^temp
   A = A^temp
End
```

Listing 1. Pseudocode for infection and β and coding scheme adaptation

The energy cost is broken down to cost due to transmissions, receptions, data processing (computing) and idle state energy:

$$E(t) = E_{TX}(t) + E_{RX}(t) + E_{CPU}(t) + E_{IDLE}(t) \tag{10}$$

All costs in equation (10) are treated cumulatively. All energy cost quantities are considered in addition to the idle state energy cost, which is taken for granted as a minimum. It has to be pointed out that transmission and reception costs are heavily affected by the overhead incurred by the error correction convolutional encoding. The computation cost expresses the energy spent by a node in order to calculate the new forwarding probability and encoding mode. We assume that, the energy amounts spent until time t are given by the expressions in equations (11).

$$E_{TX}(t) = \sum_{i=1}^{N} \sum_{t \in TXi} \varepsilon_{bitTX} k \frac{1}{R_{c,i}}, \qquad E_{RX}(t) = \sum_{i=1}^{N} \sum_{t \in RXi} \varepsilon_{bitRX} k \frac{1}{R_{c,i}}$$

$$E_{CPU}(t) = 2 \times \varepsilon_{insCPU} \sum_{i=1}^{N} \left(|RXi| + |TXi| \right) \tag{11}$$

where ε_{bitTX}, ε_{bitRX}, ε_{insCPU} are the energies spent for the transmission, reception of one bit and processing of one instruction and k is the number of bits of the infecting piece of information (or packet) that is transmitted in every transaction between two nodes. We assume that the energy spent on transmission, reception and processing is according to the Mica2 energy consumption model [15] as also adopted in [16]. Then it is possible to use (10) to calculate $h(t)$.

Simulations were run for a network of 100 randomly distributed nodes starting with a single infected node and a common forwarding probability shared by all nodes. Noise is a Gaussian distributed random variable with quite large standard deviation. The healing rate is assumed to be $\delta_i(t) = 0.1\beta_i(t)$. The fact that the healing rate is assumed to be a stable proportion of the forwarding rate excludes the possibility of the epidemic dying out, which occurs when $\delta>\beta$. The metrics defined above were measured for static β and for the adaptive schemes specified in equations (7) and (8). Both stationary and mobile nodes cases were investigated. In the mobile case, the random waypoint model was adopted.

In Fig. 1 results on the coverage rate are depicted. The quick convergence to values higher than those achieved with a static forwarding probability is evident. It can be attributed to the fact that the forwarding probability is quickly reduced from the initial value to a smooth oscillation around a lower value that allows for efficient yet effective infection. TABLE IV summarizes the advantage of various variants w.r.t. the static case in terms of efficiency improvement and energy cost gain. The cross-layer awareness of the proposed scheme clearly delivers a considerable improvement in the field of energy expenditure, especially in its sigmoid form.

It can be noted that the improvement is considerable with the linear scheme, but even more with the sigmoid one. This is related to the fact that β is suppressed more severely in the latter.

In Fig. 2 the efficiency for the sigmoid schemes is shown as a function of the original forwarding probability. The improvement compared to static schemes is dramatic in case of modest or higher original forwarding probability, where the forwarding probability is compromised more severely.

It is apparent that the efficiency of this epidemic model is maximized for medium transmission probabilities. This is intuitively justifiable, as high β values add to the infection rate but simultaneously take their toll on transmissions number.

Moreover, the impact of channel noise appears to be significant, which is as expected, since all schemes as defined in equations (7) and (8) are affected by the error rate which is enhanced by low signal-to-noise ratios. Fig. 3 indicates that noisier environments tend to keep the forwarding probabilities at higher levels, hence ensuring faster infection, however taking a toll in energy consumption (TABLE V). The slow learning curve in Fig. 3 is attributed to the high error rate. Medium SNR values display lower infection rates as a combined effect of errors and mildly suppressed β values.

TABLE IV
ENERGY COST GAIN AND EFFICIENCY IMPROVEMENT FOR THE LINEAR AND SIGMOID SCHEMES.

	ENERGY COST GAIN (%)	EFFICIENCY IMPROVEMENT (%)
linear adaptive	58.1	31.6
sigmoid adaptive	92.5	292.5

Similar conclusions are drawn for the mobile setting. As already mentioned, we assume a RWP model. Additionally we consider a homogeneous node mix i.e., each of the susceptible nodes can get in contact with any of the infected ones. Simulations have made evident (Fig. 4) that, in a mobile setting too, the proposed scheme enhances the infection process considerably, as infected nodes tend to enter the proximity of a larger number of susceptible ones. However, this comes at a cost in terms of the total number of transmissions compared to the case of static nodes. Mobile nodes discover more neighbors and attempt to infect all of them. Finally, the impact of network density is also confirmed to be considerable. As seen in Fig. 5, the benefit of adaptability seems to be stronger in dense networks, as confirmed for a static node setting.

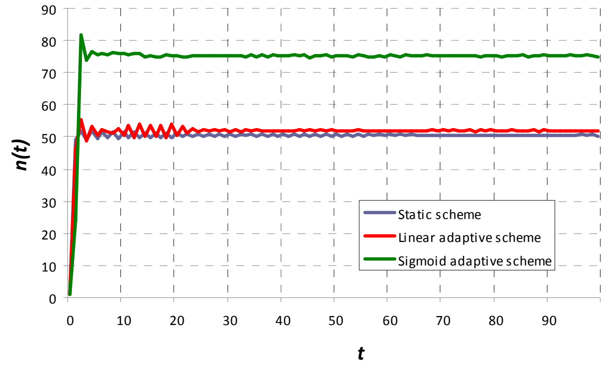

Fig. 1. Coverage rate $n(t)$ vs. time for a starting forwarding probability β_0 = 0.5

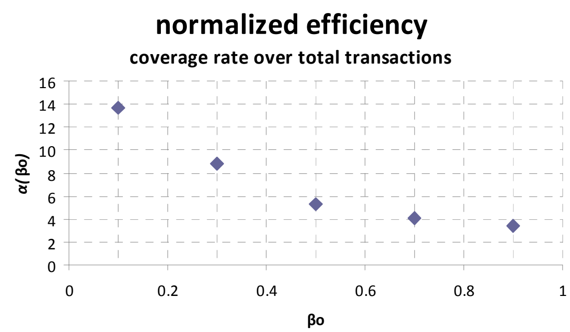

Fig. 2. Efficiency α for the sigmoid scheme vs. the original forwarding probability β_0

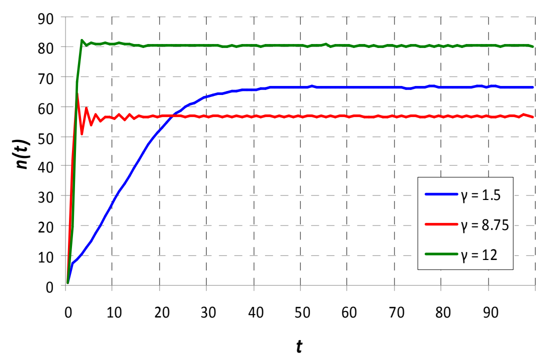

Fig. 3. Coverage rate $n(t)$ vs. time for different noise levels. The sigmoid adaptive scheme is assessed here

TABLE V.
ENERGY COST GAIN FOR DIFFERENT SIGNAL-TO-NOISE RATIOS. SIGMOID ADAPTIVE SCHEME

γ(dB)	1.5	8.75	12
Improvement (%)	92.30	12.81	83.00

VI. CONCLUSIONS AND FUTURE WORK

In this work we presented the benefits of an adaptive epidemic information dissemination scheme. At each node the forwarding rate is tuned according to the error rate and the duplicate rate. Evaluation was focused on the scheme's efficiency in infecting nodes. Higher infection rates are achieved with reduced energy expense, which is a significant advantage in an ad hoc networks and WSNs where energy tends to be scarce.

Medium values of the original forwarding probability and noise levels yield a dramatic efficiency improvement with this scheme in terms of energy expenditure and infection rate.

Original forwarding probability, noise level, mobility and network density have an impact on this scheme's performance.

In the future we would like to expand our work in models with more than one adaptive parameters, while building on the benefits of cross-layer awareness at the same.

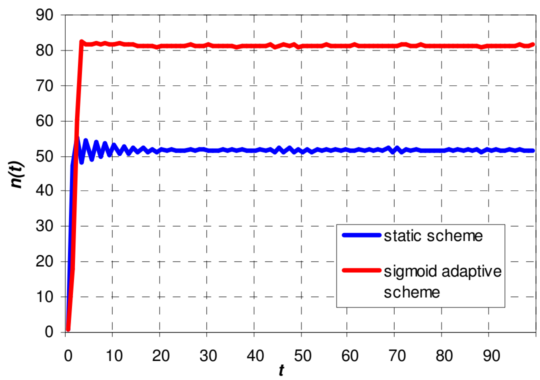

Fig. 4. Comparison of coverage rate *n(t)* vs. time for adaptive and static schemes assuming mobile nodes setting. The adaptive scheme is assumed sigmoid.

Further epidemic models are also of interest. They expand into multi-epidemic settings, and include additional, partially infected states and cater for differentiation in the disseminated data.[4]. The infecting data consists of non-identical packets, and this provides for a kind of higher-layer awareness. In such settings, larger sizes of infecting data could be considered, moving the model beyond the WSN landscape, where information of limited size is exchanged.

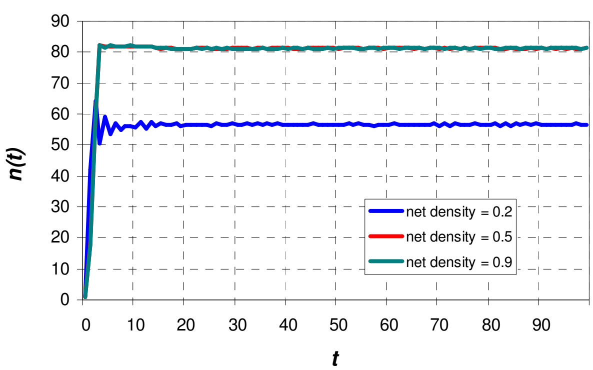

Fig. 5. Comparison of infection rates vs. time for different network densities. The various curves correspond to different normalized network densities

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