Gossiping: Adaptive and Reliable Broadcasting in MANETs ⋆

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Abstract. Given the frequent topology changes in Mobile Ad Hoc Networks (MANET), the choice of appropriate broadcasting techniques is crucial to ensure reliable delivery of messages. The spreading of broadcast messages has a strong similarity with the spreading of infectious diseases. Applying epidemiological models to broadcasting allows an easy evaluation of such strategies depending on the MANET characteristics, e.g. the node density. In this paper, we develop an epidemic model for gossiping, which is a flooding-based probabilistic broadcasting technique. We analytically investigate the impact of node density and forwarding probability on the quality of gossiping. The result of our investigation is to enable mobile nodes for dynamically adapting their forwarding probability depending on the local node density. Simulation results in ns-2 show the reliability, efficiency and scalability of adaptive gossiping.

Key words: MANET, Broadcasting, Gossiping, Reliability, Epidemic Models, Analytical Modeling

1 Introduction

Mobile Ad Hoc Networks (MANETs) are composed by mobile devices equipped with short range radios. Communication is possible between devices within each other's radio range. The mobility leads to frequent network topology changes, which complicates classical networking tasks such as broadcasting.

Network-wide *broadcasting* aims at distributing messages from the source node to all other nodes in the network. It is a major communication primitive required by many applications and protocols in MANETs. Broadcast protocols present a fundamental building block to realize principal middleware functionalities such as replication [1] and group communication [2]. Furthermore, broadcasting is frequently used to distribute information and discover or advertise resources.

Flooding is a common approach to realize broadcasting in MANETs because of its topology independency. In flooding-based approaches nodes forward a received message to all their neighbors. Subsequently, all nodes within the network should receive

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the message. Even though flooding might expose some unnecessary message overhead it should provide a robust basic strategy for broadcasting in networks with an unknown or changing topology. However, the characteristics of MANETs prohibit that a flooding process reaches every node. If the *node density*, i.e. the number of nodes operating in a given area, is too high the radio transmission will block out messages if too many nodes are rebroadcasting the received messages as it is in blind flooding. This problem is referred to as *broadcast storms* [3]. Here flooding shows a worse performance than selecting a smaller number of nodes to forward the message.

Node spatial distribution is therefore a key issue for the performance of broadcast protocols, since it determines the connectivity of the MANET. The investigation of potential MANET application scenarios shows a wide range of possible node spatial distributions and node mobilities. Therefore, a MANET generally shows a continuously changing network connectivity over space and time. Consequently, an adaptive solution for broadcasting that accounts for the heterogeneous and evolving node spatial distribution and mobility is a major contribution.

Most of the research conducted on broadcasting in MANETs has primarily focused only on carefully selected application and evaluation scenarios. Consequently, the developed broadcasting schemes do not yield good performance for other scenarios. Different comparative studies [4, 5] show that the existing broadcasting techniques are tailored to only one class of MANETs with respect to node density and node mobility, and are unfortunately not likely to operate well in other classes.

Our main objective is to provide an adaptive broadcast algorithm for a wide range of MANET operation conditions. The main contribution of this paper is *reliable gossiping*, a frugal and adaptive broadcasting technique. Reliable gossiping provides a simple mechanism for tuning the forwarding probability of gossiping depending on the local density of a node, reflected by the number of its neighbors. Reliability is a key descriptor of correctly delivered broadcast messages. Using intensive simulations in ns-2 we show that reliable gossiping can be deployed in a wide spectrum of MANETs with respect to node density, node mobility and communication range.

The remainder of this paper is organized as follows. In Section 2, we define the system model and the fault model, and outline the requirements on broadcasting in MANETs. Section 3 discusses the related work. Then, we detail the paper's objectives in Section 4. Section 5 shows how to adopt a simple mathematical compartmental model from epidemiology to analytically investigate gossiping. Using this model we show how to adapt the forwarding probability of gossiping to the local node density. In Section 6, we evaluate adaptive gossiping and compare it to related work. We conclude the paper in Section 7.

2 Preliminaries

2.1 System Model and Fault Model

In this work, we consider a MANET that is formed by N autonomous mobile nodes of similar communication capabilities (communication range R and bandwidth r). We assume that nodes may have no knowledge about their position or speed. The MANET may show a very *heterogeneous* spatial distribution of nodes, from locally very sparse to very dense, and very heterogeneous node mobility patterns, from low mobile to highly mobile. We assume that nodes acquire neighborhood information by means of HELLO beaconing.

The broadcast messages are uniquely identified, e.g. through the Media Access Control (MAC) address of the source and a locally unique sequence number. Nodes are required to store the list of IDs of messages received or originated, in a so-called *broadcast_table*. Thus nodes are able to decide, whether a received copy of a given message is the first one.

In our fault model, we consider the following communication failures: Collision, contention, frequent link breakage and network partitioning. We define network partitioning as the split of the network into two (or more) disjointed groups of nodes that can not communicate with each other. Tolerating these failures is a key issue to ensure the reliability of broadcasting.

2.2 Requirements

As node density heavily influences the performance of broadcasting, and MANETs may show a wide range of node densities, the first requirement on a broadcasting technique for MANETs is to adapt to the node density, in order to reduce broadcast storms. Global state in MANETs is hard to obtain and spatial distribution of nodes may change continuously, therefore, the second requirement on such a strategy is that nodes *independently* adapt to *local* MANET characteristics.

Furthermore, we identify two basic requirements of the applications on a broadcasting protocol, i.e. delivery reliability and delivery timeliness. In this work, we consider delay-critical applications. These applications require to efficiently reach all nodes belonging to the network partition, where the source node is located, while minimizing the message delay.

3 Related Work

The design of broadcasting is a fundamental problem in MANETs and several broadcast strategies have been proposed in the literature. In [4, 5], the authors provide two comparative studies for the existing broadcasting techniques. [4] classifies broadcasting schemes into heuristic-based and topology-based. [5] subclassifies heuristic-based class into probability-based and area-based. We categorize all these protocols into adaptive and non-adaptive protocols.

Non-adaptive heuristic-based protocols use heuristics with predefined fixed parameters to reduce broadcast storms. They do not adapt to the time-varying MANET situations that show quite different levels of broadcast storms. Examples of non-adaptive probability-based schemes are gossiping [3,6] and counter-based [3]. Examples of non-adaptive area-based schemes are location-based [3] and distance-based schemes [3]. Non-adaptive topology-based protocols (e.g. Multipoint Relaying Broadcasting [7], Connected Dominating Set Based [8], Minimum Forwarding Set Based [9], and Deterministic Broadcast [10]) require an accurate topology information which is hard to acquire in highly mobile environments and due to collisions. That is why the performance of these protocols drops for highly mobile scenarios [5] or highly congested ones.

The common drawback of all these non-adaptive broadcasting techniques is that they are optimized for specific scenarios and do not support a broader range of MANET situations [5]. In order to suit non-adaptive broadcast schemes to a broader range of operation conditions, some of them are adapted to local MANET characteristics.

In [11] the authors proposed two adaptive heuristic-based schemes, called adaptive counter-based (ACB) and adaptive location-based (ALB), and one adaptive topology-based scheme, called neighbor-coverage scheme (NC). Using a simulation-based approach the authors derived the best appropriate counter-threshold and coverage-threshold as a function of the number of neighbors for ACB and ALB respectively. The authors adapted the NC scheme by adjusting dynamically the HELLO interval to node mobility reflected by neighborhood variation, so that the needed 2-hop topology information gets more accurate. Despite this optimization, the NC scheme still has the main drawback that neighborhood information may be inaccurate in congested networks. The authors showed that these adaptive schemes outperform the non-adaptive schemes and recommend ACB if location information is unavailable and simplicity is required. We will compare our strategy to ACB in Section 6.5. [12] introduced the density-aware stochastic flooding (STOCH-FLOOD). Nodes forward messages with the following probability: $p = min\{1, 11/n\}$, where n is the number of neighbors. In [13], the authors proposed a similar scheme to STOCH-FLOOD. However, they use the counter of the message's copies received as an estimation for node density, which is obviously less accurate than the number of neighbors. Therefore, we compare our strategy to STOCH-FLOOD.

4 Objectives

With respect to broadcasting, protocol designers are interested in understanding the nature of the spreading depending on the *protocol parameters* and on the *MANET properties*. The quality of broadcasting can be expressed in the spreading progress, both in time and in space. In this work, we focus on the spreading progress in time. We define for a given message the *spreading ratio* at time t as the ratio of the number of nodes that received the message up to time t to the total number of nodes N. We denote the spreading ratio at time t by $i(t)$, with $0 \leq i(t) \leq 1$. The most relevant factors which affect the characteristics of message spreading are the parameters of the broadcast protocol and the network connectivity over space and time. The network connectivity over space and time is mainly determined by the node spatial distribution, node mobility, communication parameters (e.g., transmission range and rate), and number of nodes N.

To obtain the spreading ratio i over time t for a given broadcast protocol and a given MANET configuration, *simulations* can be used. *Analytical models* however provide the spreading ratio as a mathematical expression, e.g. $spreading\_ratio = i(t)$, which represents an elegant method to describe the spreading ratio over time. Our approach for analytically modeling broadcast protocols in MANETs consists in adjusting existing mathematical models from the epidemiology to MANET broadcasting.

Existing mathematical models that describe the spreading of epidemics can be as useful for network designers as they are for medical researchers. Medical researchers use epidemic models both to describe the spread of disease within a population and to take preventive or treatment measures. We use epidemic models both to *describe* and to *adapt* broadcasting in MANETs.

5 Modeling and Adaptation of Gossiping

In this section, we demonstrate the utility of epidemic models to adapt broadcast protocols in MANETs. For this we first detail the gossiping protocol and model it with the SI epidemic model. Then, we adapt its core parameter, the forwarding probability, to the local node density using the model.

5.1 The Gossiping Protocol

Gossiping in MANETs is simply defined as probabilistic flooding. On receiving the first copy of a given message, a node forwards the message with a fixed probability p to all nodes in its communication range using the broadcast primitive of the MAC layer. In order to reduce the collision probability, nodes delay forwarding for a random time between 0 and *fDelay*. The pseudo-code for gossiping is given by Algorithm 1. We denote by *random(x)*, a function that returns a random float value $\in [0,x]$.

Algorithm 1 Gossiping (p)

```
Var: p, fDelay
List: broadcast_table
# On receiving a DATA message M
if M.ID ∉ broadcast_table then
   # M is received for the first time
   deliver M to the application
   add {M.ID} to broadcast_table
   if random(1.0) ≤ p then
      wait (random(fDelay))
      broadcast M to all neighbors
   end if
else
   discard M
end if
```

According to this protocol, on average, only $p*N$ nodes forward the message. Thus the number of saved forwards is $(1-p)*N$. To maximize the number of saved forwards, we have to reduce the probability p. But how much can we reduce it? [6] and [14] investigated gossiping, where every node forwards a message based on a fixed probability p. In [6], the authors showed that gossiping exhibits a bimodal behavior. There is a threshold value p_0 such that, in sufficiently large random networks, the gossiping quickly dies out if $p < p_0$ and the gossiping message spreads to the entire network if $p > p_0$. Thus, ideally we would set p close to p_0 (slightly higher), and therefore save approximately a ratio of $(1 - p_0)$ forwards compared to blind flooding. [14] investigated the phase transition of gossiping in more details.

The authors in [6] identified an optimum value of $p_0 = 0.65$ for their test scenarios. Intuitively, an optimal probability for one node density may be suboptimal for other densities, so this value is not likely to be globally optimal. Furthermore, since the node density varies over time and space, we have to adjust the probability p to the local density.

Deviating from [12] [13], we do not rely on pure simulations but we use an epidemic model to determine the appropriate forwarding probability of gossiping depending on the local node density.

5.2 Epidemic Model for Gossiping

In a previous work [15] we adopted the simple epidemic SI-model to the SPIN-based broadcast protocol. In this section, we briefly summarize the main results of [15] and adopt the SI-model to the gossiping protocol.

In the SI-model, a node follows a two-state *compartmental model*: It either carries the message or not, and once "infected" by the message, a node remains infectious. The message delay of gossiping is usually in the range of milliseconds or rarely a few seconds, depending on the current network parameters and load. During this small time interval we can assume that "infected" nodes remain infectious. Consequently, we can model gossiping using the SI-model.

Let $S(t)$ denote the number of *susceptible* nodes, and $I(t)$ the number of *infected* nodes at time t. The two-state mathematical SI-model is shown in Fig. 1. Each letter in a rectangle refers to a compartment in which a node can reside.

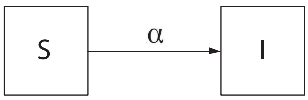


Fig. 1: Compartment diagram for the SI-model

Hereby, α is the broadcast force in the MANET. This parameter indicates the strength of the broadcasting process and has the dimension $1/time$. To develop the solution, we need to write the mass balance equations for each compartment:

$$\begin{cases} \frac{dS(t)}{dt} = -\alpha * S(t) \\ \frac{dI(t)}{dt} = \alpha * S(t) \end{cases} \tag{1}$$

The value of α is not constant, but depends on the number of susceptible and infectious nodes and the probability of transmitting the message upon encounter. We say that two nodes encounter each other if they are in each other's communication range. We define the encounter rate e as the average number of encounters per node and per unit of time. Therefore, each susceptible node makes e encounters per unit of time. Thus in total, all the susceptible nodes make $e * S(t)$ encounters per unit of time. Since we assume that nodes move autonomously, the encounters are at random with members of the total population ($N = S(t) + I(t)$). Then, only the fraction $I(t)/N$ of the encounters are with infectious individuals. Let β be the probability of message transmission in an encounter between an infectious node and a susceptible node. Then the rate of susceptible nodes that become infectious is $\beta(e * S(t))\frac{I(t)}{N}$. Thus the broadcast force is $\alpha = \frac{\beta * e}{N} I(t)$. We substitute

$$a = \frac{\beta * e}{N} \tag{2}$$

and call a the *infection rate*. As discussed in [15] with details, the solution of the system of differential equations (1) results in that the spreading ratio is:

$$i(t) = \frac{I(t)}{N} = \frac{1}{1 + (N-1) * \exp(-a * N * t)} \tag{3}$$

Eq. (2) shows that the infection rate a depends on the total number of nodes N, the encounter rate e, and the probability β of message transmission, given an adequate encounter. We note here that the encounter rate e depends on the node spatial distribution, node mobility and communication properties. β captures the impact of the communication properties and broadcast protocol parameters on the message propagation. This shows that our modeling approach is *hierarchical* which allows us to proceed *modularly* to further develop the analytical model by providing an analytical expression for a depending on the MANET properties and the broadcast protocol parameters. The calculation of a can be reduced to the determination of e from the mobility and communication models, and the determination of β from the broadcast algorithm and the communication model.

In [16], we investigated encounters between nodes in more details. We defined a set of mobility metrics based on node encounters and presented a detailed statistical and analytical analysis of these metrics for the widely used random waypoint mobility model [17] as example. In [16], we provided an analytical expression of the encounter rate (e) for the random waypoint mobility model assuming that nodes can communicate if their geographical distance is lower than the communication range: $e = R * (v_{max} - v_{min}) * d$, where R, v_{max}, v_{min} and d are the communication range in m, the maximum node speed in m/s, the minimum node speed in m/s and the node density in $1/m^2$ respectively. The analytical computation of e depends on the complexity of the considered mobility and network models.

The probability of message transmission given an adequate encounter (β) is a function of the gossiping probability (p) and the the message transmission reliability, which could be easily calculated given an appropriate analytical model for the MAC layer. In this work, we will not further consider the analytical computation. Instead of that, we use an empirical approach to calibrate our analytical model.

We proceed similarly to the epidemiologists who assume the availability of some experimental data that roughly describe the spreading of the infectious disease to calibrate the corresponding epidemic model. We rely on a few simulations to calibrate the epidemic model for gossiping. First of all, we determine the spreading ratio of gossiping for the considered MANET scenario using simulations. Afterwards, we use the *least squares method* to fit the simulation results to Eq. (3). We use the software package `mathematica` [18] to perform this fitting procedure. If the network is partitioned, we set the delay for unreachable nodes to be ∞. Therefore, the infection rate is approximately 0 for highly partitioned MANETs.

5.3 Adaptation of Gossiping

The goal of adapting gossiping is to achieve higher efficiency by reducing the number of forwarders, but without sacrificing the reliability or experiencing any significant degradation. Since the intensity of the broadcast storm depends on the local node density and may vary over time and space, we should adapt the gossiping probability p to the node's current number of neighbors, which reduces forward redundancy, contention, and collisions. In this section, we adapt gossiping to the local node density by determining the appropriate gossiping probability as a function of the number of neighbors.

Simulation Model. We use ns-2 [19] for the simulation-based performance analysis. We generate N mobile nodes in a $1km$ x $1km$ two-dimensional field, where nodes move according to the random waypoint model [17]. We vary the node speed between 0 m/s and a maximum speed value v_{max} m/s, and select a pause time uniformly between 0 and $2s$. The simulation parameters are summarized in Table 1.

Parameters	Value(s)
Simulation area	1000m x 1000m
Number of nodes	N $\in$ [50, 1000]
Comm. range	$R \in \{50, 100, 200, 300\}$m
Bandwidth	r = 1 Mbps
Message size	280 bytes
Mobility model - Max speed - Pause	Random waypoint - $v_{max} \in$ [0,30] m/s - Uniform between 0 and 2s
fDelay	10ms

Table 1: Simulation parameters

We use the following traffic model. At the beginning of the simulation (namely random between first and second sec) each of the S senders sends a single message. The simulation time selected for all scenarios in this paper is $20s$. For the adaptation process, we set $S = 1$, $R = 100m$ and $v_{max} = 3m/s$.

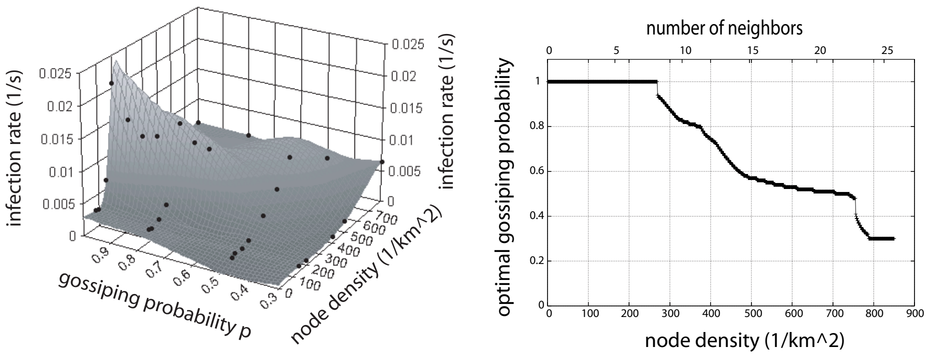
The random waypoint model shows an almost uniform node spatial distribution. This property simplifies the conversion of node density to number of neighbors and vice versa. Given n the number of neighbors and R the communication range, a node easily computes its local density by:

$$d = \frac{n+1}{\pi R^2} \Leftrightarrow n = \pi R^2 d - 1 \tag{4}$$

As mentioned before, nodes acquire neighborhood information by means of HELLO beaconing. For all simulations in this work we use a random beaconing period between $0.75s$ and $1.25s$. A node removes a neighbor from its neighbor list, if during 2s no beacon is received from this neighbor.

Adaptation Using the Epidemic Model. The infection rate a clearly depends on the gossiping probability p. If this probability is 0, the infection rate will also be 0. If p increases, the infection rate also increases. However, if the network is very dense and all nodes forward every newly received message, contention and collisions increase, so that delay increases, and subsequently the overall infection rate will decrease. Hence, we investigate the impact of both node density and gossiping probability on the infection rate in more details. This investigation allows the selection of the appropriate probability depending on node density.

According to the SI-model, the infection rate determines the spreading ratio and therefore it is a measure for delivery reliability and timeliness. The higher the infection rate, the lower the mean delay. In the following we show how we used these results to adapt gossiping. In order to adapt the forwarding probability to the node density, we should select the probability that maximizes the infection rate. We vary node density and the forwarding probability p and compute the corresponding infection rate for some combinations. Fig. 2 (a) shows the measured infection rates and their interpolation. Fig. 2 (b) shows the optimal probability, which should be used for gossiping depending on the MANET node density.



(a) Infection rate

(b) Optimal probability

Fig. 2: Adaptation of gossiping using the infection rate

Consistent with our second requirement on a broadcasting technique, we let every node set the gossiping probability *locally* and *independently*. A node j can easily estimate its local node density d_j using Eq. (4), given its number of neighbors n_j. According to the value of d_j the node sets on-the-fly the forwarding probability p_j for gossiping.

To avoid the computation of local node density, which also assumes that nodes know their communication range R, we propose that nodes select the gossiping probability depending on the current number of neighbors n. By scaling the x-axis of Fig. 2 (b) using Eq. (4), we get the optimal gossiping probability p as a function of n. We could now provide the discrete values of this curve as a lookup table that maps the number of neighbors to the probability values. At run-time, nodes could then access this lookup table in order to set the gossiping probability dynamically, depending on their current number of neighbors.

Nevertheless, in order to elegantly present our adaptation results for the community, we analytically express the gossiping probability depending on the number of neighbors. To ensure adaptation for higher dense networks, we extrapolate the gossiping probability value to higher number of neighbors. We use the following series expansion ansatz: $p(n) = a + b/n$. The fitting process using the least squares method, recommends $a = 0.175$ and $b = 6.050$. The fitting standard error is about 4.75%. The result of the adaptation is a simple function that nodes can easily use to calculate the appropriate gossiping probability (p) for the current number of neighbors (n). The function is given by Eq. (5) or simply Eq. (6):

$$\begin{cases} p = 1.0, & if\ n \leq 7 \\ p = 0.175 + 6.05/n & if\ n \geq 8 \end{cases} \quad (5)$$

$$p = min\ (\ 1.0\ ,\ 0.175 + \frac{6.05}{n}\ ) \quad (6)$$

Relevance of Epidemic Models for Protocol Adaptation. We show the relevance of the analytical epidemic models for the adaptation of broadcast protocols through investigating alternative approaches for the adaptation.

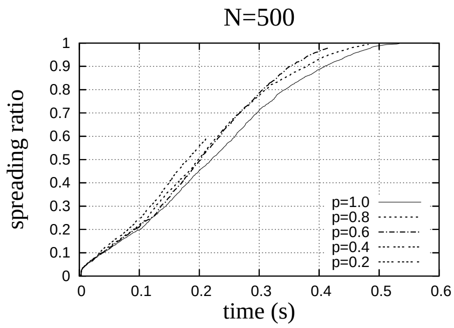


Fig. 3: Adaptation of forwarding probability (Simulation-based approach)

Fig. 3 shows the spreading ratio of gossiping over time for 500 nodes and different forwarding probabilities. We conclude that only probabilities higher than 0.6 provide a delivery reliability close to 100%. We also conclude that the forwarding probability 0.6 provides faster propagation than higher probabilities. This is due to broadcast storms if more than 60% of nodes forward the packet. Thus, investigating the spreading ratio obtained from simulations provides an alternative approach to fix the appropriate gossiping probability.

However, the selection of the probability is achieved manually and therefore it is not practical and error-prone. Furthermore, the approach requires running simulations for probability values as fine as possible to increase the accuracy of adaptation. Comparing the simulation-based approach with the approach relying on the epidemic model we note the simplicity of the last approach, which provides an automated method for the selection of the appropriate forwarding probability depending on node density, using only fewer simulations. The use of the SI-model for adaptation of key protocol parameters to relevant network properties can be easily repeated for further adaptation needs.

6 Evaluation of Reliable Gossiping

We now evaluate the adaptive gossiping protocol with scenarios that show a wide range of node densities and node speeds. Additionally, we study the impact of communication range on the performance of adaptive gossiping. We also compare adaptive gossiping with STOCH-FLOOD [12] and ACB [11]. Our evaluation approach is simulation-based.

We use the same simulation model as in Section 5.3. We set the number of senders to $S = 25$. Since the knowledge of the partitioning of the MANET is important for understanding the performance of adaptive gossiping, we computed the average number of partitions for the different scenarios that we consider in this section (Fig. 4). For this computation we use our own framework presented in [20].

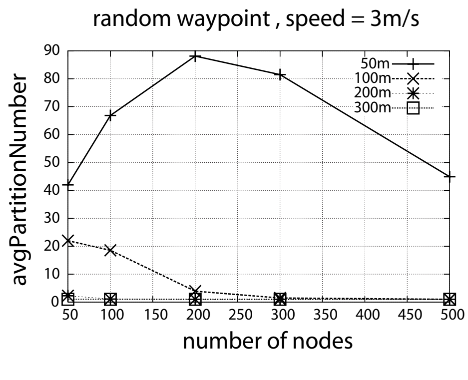


Fig. 4: Average number of partitions

6.1 Performance Metrics

In order to evaluate broadcast protocols with respect to delivery reliability and timeliness, the performance metrics reachability and delay respectively are commonly used in the broadcast community. In the following we define these both metrics. With respect to a given broadcast message, we denote by *#Forwd* the number of nodes that forwarded the message and by *#Reach* the number of nodes that received the message after the termination of the protocol.

REachability (RE): The ratio of nodes receiving the message to the total number of nodes, i.e. $RE = \frac{\#Reach}{N}$ ($\in [0,1]$). The reachability metric measures the delivery reliability.

Delay: Average end-to-end delay over all receivers. Denoting by t_s the origination time of the message and by t_j the arrival time of the message at node j, we calculate the delay as follows: $delay = \frac{1}{\#Reach} \sum_{reachedNode_j} (t_j - t_s)$.

To evaluate the efficiency of broadcast protocols the message complexity is a key factor. The common efficiency metric for broadcast protocols is:

MNF: Mean Number of Forwards per node and message. $MNF = \frac{\#Forwd}{N}$.

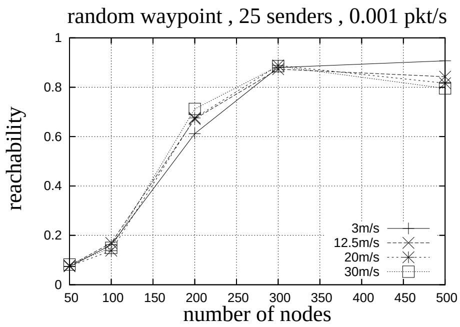
As we used the spreading ratio for describing the quality of a broadcast protocol, we differentiate the above metrics from the spreading ratio. Both metrics RE and $delay$ are easily gained from the spreading ratio. Given the spreading ratio as a time function $i(t) \in [0,1]$. The RE is the the maximum value of the spreading ratio (reached when the broadcast protocol terminates), or $RE = \max(i(t))$. The delay is calculated as follows: $\frac{1}{RE} \int_0^{RE} i^{-1}(t)\, dt$, where $i^{-1}(t)$ is the inverse function of $i(t)$.

6.2 Impact of Node Density and Node Mobility

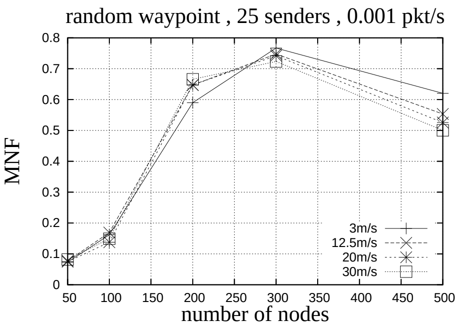
For this study, we vary the node density by tuning the total number of nodes and keeping the area unmodified. From Fig. 5 (a), we observe that the reachability of adaptive gossiping first increases with node density, reaches a maximum and then starts to decrease. We qualitatively explain this effect as follows: Obviously, gossiping can only reach nodes that belong to the partition, which contains the source node. For random waypoint, the mean number of partitions decreases with the increasing number of nodes (Fig. 4, 100m range). This means that the average partition size is increasing. Therefore, reachability increases with the increasing number of nodes. For high number of nodes, collision probability becomes higher and the reachability begins to decline slightly.

The impact of node speed is marginal. However, we present three observations. Firstly, for very sparse networks the mobility has no impact on the reachability. Secondly, for scenarios that are neither very sparse nor connected (e.g. 200 nodes), the mobility may help to overcome network partitioning and the reachability increases with higher speeds. Thirdly, for dense scenarios, reachability decreases with higher speeds. The reason is that a node may sense a free carrier and starts to transmit; but while moving very fast it disturbs other ongoing transmissions.

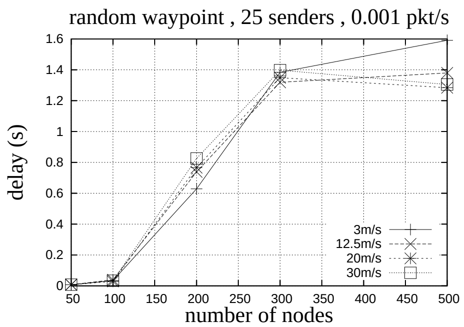
In Fig. 5 (b), we show the message overhead (MNF) of adaptive gossiping. For random waypoint, we can assume a uniform node distribution, and therefore estimate the MNF of gossiping as follows: $MNF \approx p * RE$. This explains the behavior of MNF, which shows a strong similarity to that of reachability. For lower number of nodes, The



(a) Reachability



(b) MNF



(c) Delay

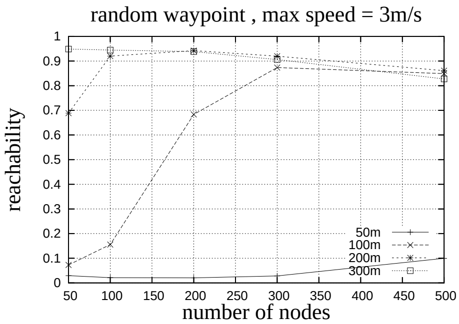
Fig. 5: Impact of node density and speed

forwarding probability p is frequently set to 1.0 and $MNF \approx RE$. For higher number of nodes, nodes use lower forwarding probabilities, thus increasing the number of saved forwards, and therefore $MNF < RE$. The delivery delay increases with increasing number of nodes since the number of traversed hops to the destination and the buffering time of messages at the MAC layer increase (Fig. 5 (c)).

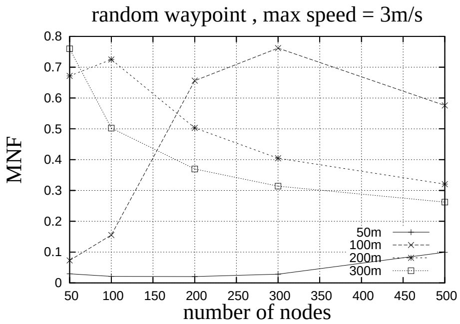
6.3 Impact of Transmission Range

In this study, we investigate the performance of gossiping for different communication ranges $\in \{50, 100, 200, 300\}m$. We note that an increase in communication range can be interpreted as an increase of node density.

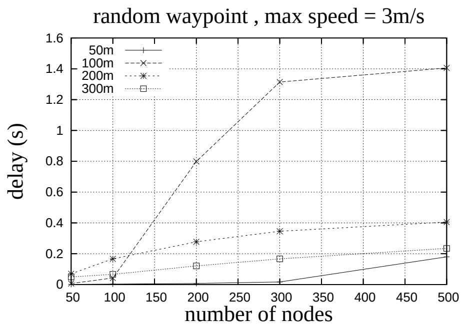
The reachability of gossiping increases with the communication range (Fig. 6 (a)). For low communication ranges, the reachability decreases with increasing number of nodes and reaches a minimum (by $N = 200$ and for $R = 50m$), and increases for higher numbers of nodes. We explain this decrease of reachability as follows. For highly sparse MANETs, an increase of number of nodes, leads to a decrease in the ratio of partition size to the total number of nodes. Consider the extreme case, where nodes are isolated and the reachability of gossiping is $1/N$. If we increase the number of nodes by δN and all nodes remain isolated, the reachability of gossiping is $1/(N+\delta N)$. Therefore, the reachability of gossiping decreases with increasing number of nodes in highly sparse MANETs.



(a) Reachability



(b) MNF



(c) Delay

Fig. 6: Impact of transmission range

For higher communication ranges, the curve of reachability however shows a maximum. The reachability slightly decreases for higher numbers of nodes due to the increasing number of collisions. The number of collisions increases since most of source nodes are within each other's communication range. Therefore, one broadcast has more impact on the other broadcasts taking place almost simultaneously. Gossiping has not been adapted to network load. Consequently, for higher network loads the reachability of gossiping is likely to decrease.

For discussing the message overhead, we first consider the communication range 100m (Fig. 6 (b)). MNF first increases with the number of nodes, reaches a maximum and then decreases. The maximum is reached, when almost all nodes forward broadcast messages, i.e. gossiping goes into blind flooding. MNF reaches its maximum, when the MANET starts to be constituted of one large partition and a few small partitions. If the MANET node density increases, adaptation of gossiping runs and saves a number of forwards, which is reflected by the decrease of MNF. For the 200*m* communication range, the maximum is reached for 100 nodes. For a 300*m* communication range the maximum moves to the left of 50 nodes and is no longer observed for our experiment settings. For a 50*m* range, MNF is very close to reachability, since the node density is very low and almost all receivers forward messages. The maximum is reached for a number of nodes that is higher than 500 nodes.

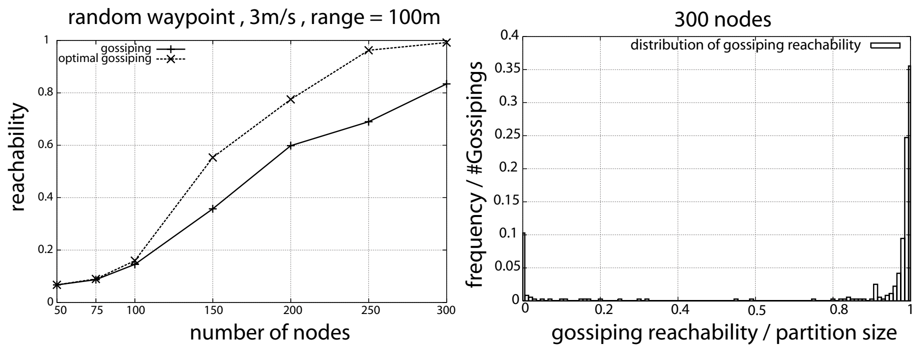
We note that the performed delay should be interpreted relatively to the achieved reachability. Fig. 6 (c) shows that the delay decreases with an increasing communication range (except for 50*m*). The explanation is that: If the communication range gets higher, a transmission is more likely to reach more nodes, which decreases average delay. We observe however that the delay for 50*m* is lower than that for higher communication ranges. This is due to the fact that, for 50*m* the MANET is highly partitioned (Fig. 4) and a network partition is composed of few nodes. Gossiping reaches these few nodes in a few transmissions, i.e. very fast. Similarly, we explain the low delay values for 100*m* range and number of nodes less than 100.

6.4 Comparison of Reliable Gossiping to the Optimal Case

From the above studies, we realize the strong need for a global view with respect to network partitioning in the MANET for a better understanding of the protocol performance. In [20], we presented the utilities required for ns-2 users, in order to simplify the access to this global view. In the following, we present the global evaluation of reliable gossiping.

Reliable gossiping aims to efficiently reach all nodes in the partition where the broadcast source is located. In this section, we aim to investigate in more details the delivery reliability of gossiping. In particular, we define the optimal gossiping reachability (OG_RE) as the ratio of the size of the partition containing the gossiping source node to the total number of nodes: $OG\_RE = \frac{partition\_size}{N}$.

The reachability of adaptive gossiping should correlate with the partition size. Fig. 7 (a) shows that the gossiping reachability is lower than the optimal gossiping reachability and that the difference is more important for higher number of nodes. This is due to collisions, which prohibit gossiping from progressing, and become more frequent with increasing number of nodes. Fig. 7 (b) shows the frequency histogram of the ratio of the number of nodes reached by gossiping to the sender's partition size. We observe that in most of cases gossiping reaches either more than 90% of the partition nodes or less than 10% of nodes, which proves the transitional behavior discussed in [6] [14].



(a) Reachability (b) Frequency histogram

Fig. 7: Comparison of reliable gossiping to the optimal case

6.5 Comparison to Related Work

We compare the performance of our adaptive scheme to that of the Adaptive Counter Based scheme (ACB) [11] and of stochastic flooding (STOCH-FLOOD) [12]. We arbitrarily fix v_{max} to 3 m/s. However, we vary the total number of nodes N.

The ACB scheme uses a random time span to count redundant packet receptions and forwards the message after this span, only if the counter value is below a threshold value. This time period is comparable to the random forwarding delay of gossiping ($fDelay$) and STOCH-FLOOD. Therefore, we choose the same value for all three protocols, i.e. 10ms, which is also used in [5]. The adaptive thresholds for all three protocols are shown in Fig. 8.

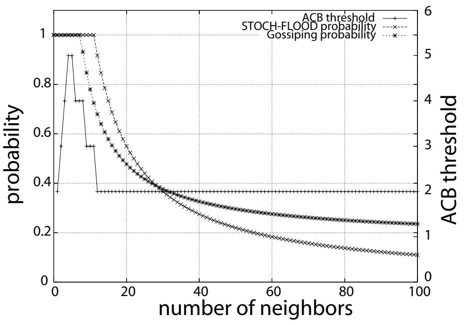
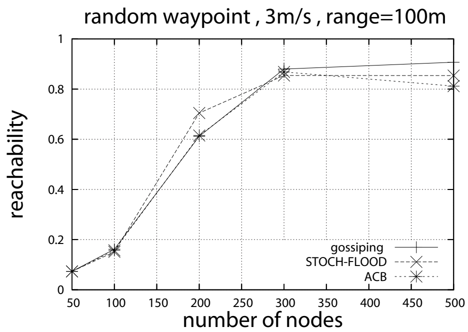
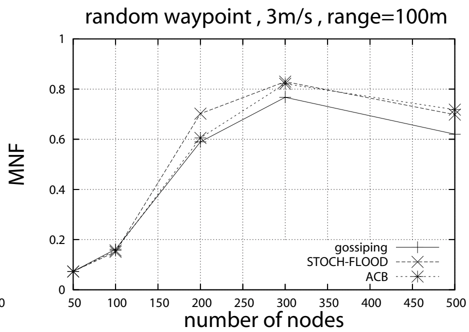


Fig. 8: Adaptive thresholds

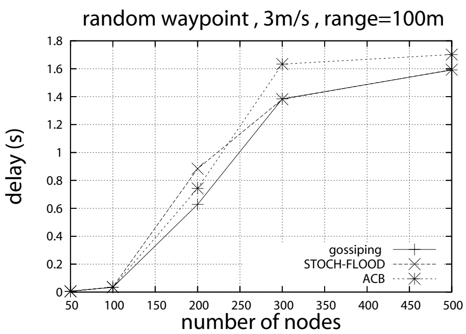
The comparison of reliable gossiping to STOCH-FLOOD can be intuitively undertaken based on the comparison of probability functions used by each protocol (Fig. 8). Reliable gossiping starts decreasing the forwarding probability for a number of neighbors equal to 8 or higher. However, STOCH-FLOOD starts decreasing the probability from 11 neighbors. Up to 28 neighbors gossiping uses a lower probability than that of STOCH-FLOOD. Therefore, both reliable gossiping and STOCH-FLOOD perform very comparably with respect to reachability and delay (Fig. 9 (a) (c)).



(a) Reachability



(b) MNF



(c) Delay

Fig. 9: Comparison of reliable gossiping to related work

We observe that adaptive gossiping has a slightly higher reachability than both ACB and STOCH-FLOOD for higher numbers of nodes. This is due to the fact that adaptive gossiping uses lower probability value than STOCH-FLOOD and that ACB stops to tune the counter threshold for higher node densities. Compared to ACB, gossiping shows a comparable reliability and a slightly lower delay. The MNF of adaptive gossiping is slightly lower than that of STOCH-FLOOD and ACB (Fig. 9 (b)). We observe that ACB has the lowest reachability, the highest message overhead and the highest delay for higher number of nodes (500 nodes). This also due to that ACB stops adjusting the counter threshold for higher number of nodes (Fig. 8).

Summarizing, we can roughly conclude that adaptive gossiping shows a very comparable overall performance to STOCH-FLOOD and that both protocols outperform ACB and particularly in highly dense scenarios. Between adaptive gossiping and STOCH-FLOOD, we identify the following marginal differences. In extremely dense networks, STOCH-FLOOD saves more forwards and reaches slightly more nodes than adaptive gossiping. However, in less dense scenarios adaptive gossiping saves more forwards and reaches slightly less nodes than STOCH-FLOOD.

Simulation results that we do not include here show that the three protocols achieve a very comparable performance for further mobility models such as the reference-point group mobility model [21] and the graph-based mobility model [22], which show quite different node spatial distributions.

7 Conclusions

We showed at the example of gossiping, how to use epidemic models to adapt broadcasting strategies in MANETs. We used the analytical epidemic model developed for gossiping to adapt the main parameter of gossiping, i.e. the forwarding probability, to the most relevant MANET property, i.e. node density. The result is a reliable broadcast protocol that adapts locally to the continuously changing node spatial distribution. Gossiping dynamically adjusts the forwarding probability only based on the number of neighbors, a locally available information, and without requiring any particular information, such as distance, position, or velocity.

Intensive simulations show the near-optimal reliability of adaptive gossiping. Furthermore, the dynamic selection of the forwarding probability reduces the total number of nodes forwarding a certain message, thus effectively alleviating the broadcast storm problem. We additionally highlight the simplicity, frugalness and scalability of our protocol. Adaptive gossiping performs very comparably to the few adaptive broadcast schemes known from the literature. This shows the applicability of the analytical platform we developed for the adaptation of MANET broadcast protocols. Particularly, we emphasize that the use of the SI-model for adaptation of further protocols to further relevant MANET properties can be easily repeated.

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