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On the Information Propagation in Mobile Ad-hoc Networks Using Epidemic Routing

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***Abstract*—In this paper, we study information propagation in a 2D mobile ad-hoc network, where mobile nodes are randomly and independently distributed on a torus following a homogeneous Poisson process with a given density. Nodes in the network move following a random direction mobility model. A piece of information is broadcast from a source node to all other nodes in the network, using a Susceptible-Infectious-Recovered (SIR) epidemic routing protocol. A distinguishing feature of the SIR algorithm, which leverages the mobility of mobile users, is that a relay node carries and forwards a piece of information for a specified amount of time. We first propose a metric fundamentally characterizing the information propagation in mobile ad-hoc networks. Then analytical results are derived for the probability that a non-zero fraction of nodes receive the information in the limit of large network size and for the expected fraction of nodes that receive the information. The analytical results are verified using simulations. The research provides useful insights on the design of mobile ad-hoc networks.**

***Index Terms*—mobile ad-hoc networks, connectivity, epidemic routing, percolation**

I. Introduction

A mobile ad-hoc network (MANET) [1] is a self-organizing network composed of mobile devices with wireless communication capabilities, such as PDA or smart phones. A prospering application of MANET is the mobile social network. In a mobile social network, the information dissemination relies not only on the mobile broadband connection between mobile users and the base stations, but also on the local ad-hoc connections between mobile users that emerge as these mobile users move and meet each other. We focus on the latter method, i.e. ad-hoc method, of the information dissemination in this paper. The ad-hoc method of information dissemination in mobile social networks can reduce the resource usage of the base station and so lower the cost for content providers and users by utilizing cheaper radio resources, such as Bluetooth or cognitive radio, and physical mobility of the mobile users. Ad-hoc data routing algorithms for mobile social networks have been widely studied [2].

The topology of a MANET is usually similar to the topology of a human network, in the sense that the mobility of nodes in a MANET is not only similar to, but often governed by, the movements of their human owners. Just as humans can only transmit infection to others in their vicinities, their ad-hoc wireless devices can only communicate with other wireless devices within a small radio range. In addition, the wireless link between two devices is intermittent due to the movements of mobile users. It follows that there may not (always) be a path between two users at any time instant. Therefore many commonly used routing protocols (e.g. AODV [3], DSR [4] or a flooding broadcast algorithm [5]), that can only disseminate information to the node(s) that is connected to the source by at least one path at a particular time instant, are actually not suitable for MANETs.

In view of the failure of traditional routing protocols and the similarity between MANETs and human networks, epidemic routing algorithms [6] have been proposed as an efficient and reliable approach to disseminate information in MANETs. An epidemic routing algorithm adopts the so-called *store-carry-forward* paradigm, where a node stores and carries its received information then forwards it to the neighbors when the direct links to them emerge. As a consequence of the store-carry-forward paradigm, the information is forwarded from a source to a destination using a journey instead of a path, where a *journey* is an alternation of packet transmissions and carriages, that connects a source to a destination [7]. The epidemic routing algorithm well leverages the mobility of nodes and efficiently disseminates information in MANETs. In this paper, we consider the broadcast of a piece of information using a Susceptible-Infectious-Recovered (SIR) epidemic routing algorithm [8], which is introduced in detail in Section III, as a typical example to study the information propagation process in a MANET and the connectivity properties of the MANET using epidemic routing algorithms.

One of the most fundamental properties of wireless ad-hoc networks is connectivity [9], [10]. In a *static network* (whose topology does not change over time), two nodes are said to be *connected* iff (if and only if) there is at least one path between them. There has been significant research on the properties of connectivity of static networks in the last few years [9],

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[10]. Different from a static network, in a MANET two nodes are said to be *connected* iff there is at least one journey between them. As illustrated in Fig. 1, node A is connected to node D. However, node D is not connected to node A. Further, previous research on static networks has shown that it is either unnecessary or impractical to require every pair of nodes to be connected [11], [12]. This observation is also valid in a MANET [13]. It follows that one of the most important performance metrics for the information dissemination in a practical wireless ad-hoc network is the number of nodes that successfully receive the information sent from a source node. To study this performance metric, recent research has focused on the percolation probability and the phase transition phenomenon [14]. In this paper, we study the connectivity properties of a MANET from the aspect of percolation, which is introduced in detail in Section IV.

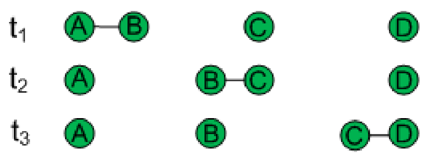

Fig. 1. Illustration of a MANET with four mobile nodes at three different time instants. There is a direct link between nodes A-B, B-C and C-D at time t_1, t_2 and t_3 respectively.

In this paper, we first discuss the *definitive metric* for the information propagation process in a MANET, which is determined by various parameters such as node density, mobility, radio range, etc. We propose a single metric that captures the impact of various parameters. Then using the definitive metric, analytical results are derived for the probability that a non-zero fraction of nodes receive the information broadcast from an arbitrary source node in the limit of large network size. Further, we provide the expected fraction of nodes that receive the information.

The rest of this paper is organized as follows: Section II reviews related work. Section III introduces the network model, mobility model and the epidemic routing algorithm used in this paper. The analytical results are derived in Section IV. Section V validates the analysis using simulations. Finally Section VI concludes this paper and proposes possible future work.

II. Related work

Early studies on the connectivity of mobile ad hoc networks were based on the definition of connectivity only suitable for static networks, i.e. a network is said to be (always) connected iff there exists a path between every pair of nodes at any time instant. In [15], Santi studied the critical transmission range (CTR) for a MANET to be (always) connected, where nodes are uniformly distributed in a unit square and move following the random waypoint mobility model. The author showed that the CTR of the MANET is larger than that of a static network. This is because the random waypoint mobility model he adopted does not preserve the stationarity of node distribution over time. Specifically, the density of nodes becomes higher in the center of the area and is lower at the boundary. Therefore the CTR needs to be increased in order to connect the nodes at the boundary who suffer from a lower locally node density.

Different from the random waypoint mobility model, there are mobility models that preserve the stationarity of node distribution over time, e.g. the random direction model (RDM) and random walk model (RWM) [16], [17]. In [18], Diaz et al. studied the expected length of the connected (disconnected) period, i.e. the time period during which an initially connected (disconnected) network remains connected (disconnected), in a MANET where nodes are uniformly distributed on a unit torus and move according to the RWM. They adopted the unit disk communication model (i.e. two nodes are directly connected iff their Euclidean distance is smaller than or equal to the radio range r_0) and the radio range is set to be the CTR. Note that the CTR of a MANET under the RWM is the same as the CTR of a static network with a same node distribution, because the RWM preserves the stationarity of the node distribution over time. In [17], Groenevelt et al. studied the end-to-end message delay in a MANET using an unrestricted multicopy protocol alike broadcasting. Using several mobility models, including RWM and RDM, they showed that the successive meeting time of two nodes approximately follows an exponential distribution. This *exponential inter-meeting time* has been used as a basic assumption in much later research in this area (e.g. [19], [20]).

There are studies on the connectivity properties based on the underlying graph of a MANET. An *underlying graph* of a MANET over time $[0, t]$ is defined [7], [19] to be an undirected graph where each vertex uniquely represents a node and each link uniquely represents a wireless link between two nodes, if the link exists in *any* time instant during time $[0, t]$. In [19], Pellegrini et al. studied the time taken for the underlying graph to be connected for a MANET where nodes are uniformly distributed in a square area and nodes move in a way that results in an exponential inter-meeting time. However, it is trivial to show that the connectivity of the underlying graph does not imply the connectivity of a MANET.

In view of the special characteristics of MANETs, epidemic routing algorithms [6] have been proposed to disseminate information in MANETs. A survey on various kinds of epidemic routing algorithms are provided in [21]. In [20], Zhang et al. studied the performance of several epidemic routing algorithms in MANETs using the assumption of exponential inter-meeting time between nodes. They provided ordinary differential equations for several performance metrics for several types of epidemic routing algorithms. From the aspect of epidemiology, Britton [8] presented a comprehensive survey on stochastic epidemic models, which inspires us with many ideas that can be brought into the study of MANETs. Different from the study of how to stop a disease in epidemiology, we study how to disseminate information to the network by tuning the metrics that might be more relevant to wireless ad-hoc network engineers, such as radio range or active period that will be introduced later.

III. System model

A. Network model

Consider a MANET where nodes are randomly and independently distributed on a torus $(0, L]^2$ [14] following a homogeneous Poisson point process with intensity λ. Two nodes are directly connected iff their Euclidean distance is smaller than or equal to the radio range r_0. Note that we will let $L \to \infty$ in Section IV-B to study the information propagation in a MANET in the limit of a large network size. However, the analytical results reported in this paper are fairly accurate as long as L is larger than the minimum value given in Section IV-A, as shown by simulation in Section V.

Further, the nodes in the network move according to the RDM introduced in [16]. Specifically, each node chooses its direction independently and uniformly in $[0, 2\pi)$, and then move thereafter at a constant speed V common to all nodes. The impact on the information propagation process of other mobility models, e.g. incorporating time variations of speed and direction, can be readily studied following the analysis outlined in the paper, which is left as our future work.

It is worth noting that under the aforementioned node distribution model and RDM mobility model, the spatial distribution of the nodes always follows a homogeneous Poisson point process with intensity λ at any time instant [17].

B. Susceptible-Infectious-Recovered (SIR) routing algorithm

Consider a basic stochastic SIR epidemic routing algorithm [8], where a piece of information starts to broadcast from a source node. Note that the source node can be any node in the network without affecting the results, because of the homogeneous and stationary Poisson distribution of the nodes.

By analogy to the way a disease spreads in a human network, a node in the MANET can be in any of the three states S, I, R: A node that has never received the information from the source is in the state of susceptible (S), in which the node can accept incoming transmissions if such opportunity arises. A susceptible node goes into the state of infected and infectious (I) immediately after it has received a copy of the information. The node in state I will keep transmitting the information, i.e. remain infectious, for a certain time period τ, which is referred to as the *active period*. After the active period the node enters into the state of recovered and immune (R). A node in state R will stop transmitting the information to other nodes and will also ignore all future transmissions of the same information from other nodes. Note that the state S resembles the situation that a node cannot broadcast a piece of information before receiving it. The reason for the transition from state S to I is that every node acts as a relay that starts to forward an information after receiving it. Further, the transition from state I to R after a certain time period is a reflection that in reality a wireless device will not keep re-transmitting the same information indefinitely; doing otherwise would result in a huge waste of resources such as network bandwidth and device battery.

Finally, the SIR information propagation naturally stops (i.e. reaches the *steady state*) when there is no infectious node in this network. Note that the SIR routing algorithm is a distributed algorithm which does not require any form of central control or route table maintenance. Therefore the SIR routing algorithm is suitable for dynamic network topologies such as MANETs. We study the performance of the information propagation using an SIR routing algorithm by studying the steady state fraction of informed nodes, where the *informed nodes* are the nodes that have ever received the information.

A distinguishing feature of the SIR algorithm, which leverages the mobility of mobile users, is that a relay node carries and forwards a piece of information for a specified amount of time (i.e. the active period), whereas a relay node using a traditional flooding broadcast algorithm [5] only forwards a piece of information once. A longer active period leads to an increase in the fraction of informed nodes. On the other hand, a longer active period also causes a larger demand on various resources such as bandwidth, device memory, device battery, etc. In the design of a MANET using the SIR epidemic routing algorithm, the choice of the active period is a major issue, as will be seen in Section V.

IV. Analytical results

The information propagation process of a MANET is determined by various parameters such as node density, mobility, radio range and the length of active period. We first propose a single metric that captures the impact of various parameters.

A. The definitive metric

As introduced in Section I, the topology of a MANET is similar to the topology of a human network. Inspired by the analysis in epidemiology [8], we introduce a metric named the *reproductive rate* R_0, which is the expected number of susceptible nodes that have been inside an infectious node's radio range during the infectious node's active period, to capture the impact of various parameters on the information propagation process.

Under the RDM, as illustrated in Fig. 2, the size of the area covered by the radio range of an infectious node during time $t = \tau$ is $A = 2r_0V_*\tau + \pi r_0^2$, where $V_* = \frac{4V}{\pi}$ is the average relative speed between two nodes moving according to the RDM. Therefore the reproductive rate under RDM is

$$R_0 \le 2r_0V_*\tau\lambda + \pi r_0^2\lambda = \frac{8r_0V\tau\lambda}{\pi} + \pi r_0^2\lambda \tag{1}$$

where the right hand side of the inequality is the expected number of nodes in the area of size A. The use of an inequality rather than an equality is due to two factors: i) It is possible that an infectious node's trajectory overlaps itself during the active period, for the node moving on a torus with a small area. ii) The nodes that move into the radio range of an infectious node may not all be susceptible nodes. The first problem will disappear if we consider a large enough network area, i.e. $L \ge V\tau + 2r_0$. The second factor suggests that R_0 is a time-varying parameter. For analytical tractability, we use the upper bound of the reproductive rate. The impact of this approximation will be discussed later in Section V.

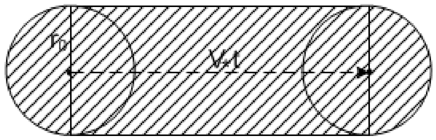

Fig. 2. Illustration of the area (shaded) covered by the radio range of a moving node during time t under the random direction mobility model.

It is worth noting that the metric R_0 reflects various parameters including node density, node moving speed, radio range and active period. It is shown later in Section V that the metric R_0 well captures the impact of various parameters on the connectivity properties of a MANET.

B. Percolation probability

In a static network, the *percolation probability* is the probability that a source node is contained in a connected component of an infinite number of nodes, as the number of nodes in the network goes to infinity [14]; here a connected component is a maximal set of nodes in which every pair of nodes is connected by at least one path. Accordingly, we study the percolation probability of a MANET in the limit of large network size in this subsection, where *in the limit of large network size* means that we increase the network area to infinity (i.e. let $L \to \infty$) while keeping other parameters, e.g. the node density and all distance measurements, constant. This is in analogy to the extended network model of static networks [14]. With a slight abuse of terminology, we say that the *percolation probability* of a MANET is the probability of having a non-zero fraction of informed nodes in the steady state, in the limit of large network size.

Similarly to the analysis in epidemiology [8], we study the percolation probability in a MANET by studying the probability that the information propagation does not become extinct at the beginning of the information propagation process. Specifically, we model the beginning of the information propagation process by a Galton-Watson branching process [22]. As illustrated in Fig. 3, the root of the branching process is the source node. In the construction of the branching process, a node (B) is "born" as an offspring of a node (A) iff it receives the information *for the first time* from node A. It is obvious that the expected number of offspring of a node is given by the reproductive rate R_0. It can be shown, according to [8], that the reproductive rate R_0 can be well-approximated by its upper bound, because there are few informed nodes in the network at the beginning of the information propagation process. Therefore, in this subsection, we consider the network that only consists of susceptible nodes only.

We first study the extinction probability q of the branching process in Lemma 1, where the *extinction probability* [22] is the probability that the steady state expected fraction of informed nodes goes to zero asymptotically in the limit of large network size.

Lemma 1. *Given the reproductive rate R_0, the extinction probability is $q = \frac{W(-R_0 e^{-R_0})}{-R_0}$, where $W(.)$ [23] is the Lambert W-Function.*

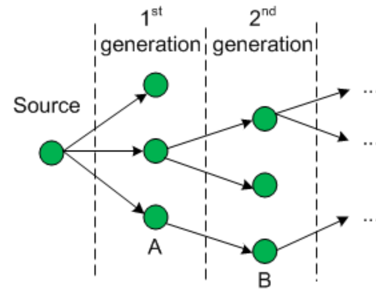

Fig. 3. Illustration of a branching process which represents an information propagation process in a MANET.

Proof: In a branching process, the extinction probability q is the smallest solution of $q = E(q^{R_s})$, where R_s is the number of nodes that come into the radio range of an infectious node during its active period [22, Theorem 6.5.1]. Note that the metric R_0 is the average value of R_s, i.e. $R_0 = 2r_0V_*\tau\lambda + \pi r_0^2\lambda$ at the beginning of the information propagation process.

Denote by $f_n(n)$ the pmf (probability mass function) of the number of nodes in the area (of size $A = 2r_0V_*\tau + \pi r_0^2$). Due to Poisson distribution of nodes, we have:

$$E(q^{R_s}) = \sum_{n=0}^{\infty} q^n f_n(n) \quad (2)$$

$$= \sum_{n=0}^{\infty} q^n \frac{(A\lambda)^n e^{-A\lambda}}{n!} \quad (3)$$

$$= e^{-A\lambda} \sum_{n=0}^{\infty} \frac{(qA\lambda)^n}{n!} \quad (4)$$

$$= e^{-A\lambda} e^{qA\lambda} = e^{-R_0} e^{qR_0} \quad (5)$$

Therefore, q is the smallest solution to $q = e^{-R_0}e^{qR_0}$. Solving the equation, it can be obtained that $q = \frac{W(-R_0e^{-R_0})}{-R_0}$, where $W(.)$ [23] is the Lambert W Function. ■

Given the reproductive rate R_0 and the extinction probability q, it is straightforward to obtain the percolation probability, which is a connectivity property similar to the probability of disease outbreak in epidemiology [8].

Corollary 2. *Given the reproductive rate R_0, the percolation probability is $1 + \frac{1}{R_0}W(-R_0e^{-R_0})$.*

Proof: Recall that the percolation probability is the probability of having a *non-zero* steady state fraction of informed nodes, in the limit of large network size. Then according to the definition of extinction probability q, it is straightforward that the percolation probability is $1 - q = 1 + \frac{1}{R_0}W(-R_0e^{-R_0})$. ■

C. Expected fraction of informed nodes

Denote by z_0 the steady state expected fraction of informed nodes, i.e. the expected fraction of nodes that have received the information before the epidemic information propagation stops. Lemma 3 gives the steady state expected fraction of informed nodes.

Lemma 3. *Given the reproductive rate R_0, the steady state expected fraction of informed nodes is $z_0 = 1 + \frac{1}{R_0}W(-R_0e^{-R_0})$, where $W(.)$ is the Lambert W Function.*

Proof: We use the ordinary differential equations (ODEs) to solve the expected fraction of informed nodes. Let $s(t)$, $i(t)$ and $r(t)$ denote the fraction of nodes in the state of S, I and R respectively. When the number of nodes in the network is large, the information propagation process is traditionally approximated by the classic SIR rate equations [8]:

$$s'(t) = -\beta s(t)i(t) \quad (6)$$

$$r'(t) = \frac{1}{\tau}i(t) \quad (7)$$

where β is the expected number of susceptible nodes that come in to an infectious node's radio range during a unit time interval. It is trivial to show that $\beta\tau = R_0$.

Combining Eq. 6 and Eq. 7, we have:

$$\frac{ds(t)}{dr(t)} = -\beta\tau s(t) = -R_0 s(t) \quad (8)$$

The solution of the above equation can be readily obtained: $s(t) = C_1 e^{-R_0 r(t)}$, where C_1 is a constant. Because $s(0) = 1$ and $r(0) = 0$, we have $C_1 = 1$. Because there is no infectious node when the information propagation stops and all the nodes that have ever received the information are in state R, we have $r(\infty) = z_0$ and $s(\infty) = 1 - z_0$. Therefore $1 - z_0 = e^{-R_0 z_0}$.

Therefore $z_0 = 1 + \frac{1}{R_0}W(-R_0e^{-R_0})$, where $W(.)$ is the Lambert W Function [23]. ■

Finally the following theorem summarizes the major results of this paper:

Theorem 1. *Consider the broadcast of a piece of information from an arbitrary source node using the SIR epidemic routing algorithm, with the reproductive rate R_0. Denote by z_0 the steady state expected fraction of informed nodes. If $R_0 \leq 1$, then $z_0 \to 0$ in probability asymptotically in the limit of large network size. If $R_0 > 1$, then $\Pr(z_0 = 0) = \frac{W(-R_0e^{-R_0})}{-R_0}$ and $\Pr(z_0 = 1 + \frac{1}{R_0}W(-R_0e^{-R_0})) = 1 + \frac{1}{R_0}W(-R_0e^{-R_0})$.*

Proof: This theorem is readily obtained using Lemma 1, Lemma 3 and the threshold theorem in epidemiology [8]. The threshold theorem states that in a SIR epidemic model with m initial infectives and $n - m$ initial susceptibles, if $R_0 \leq 1$, then $z_0 \to 0$ in probability as $n \to \infty$. On the other hand, if $R_0 > 1$, then $\Pr(z_0 = 0) = q^m$ and $\Pr(z_0 = z) = 1 - q^m$, where z is the value calculated in Lemma 3 of this paper. ■

V. Simulation Results

In this section, we report on simulations to validate the accuracy of the analytical results. The simulations are conducted using a MANET simulator written in C++. Nodes are randomly and independently deployed on a torus $(0, 600]^2$ following a homogeneous Poisson process with intensity $\lambda = 0.003$. Therefore, the expected number of mobile nodes in the network is 1080. After deployment of the nodes, they start to move according to the mobility model introduced in Section III. The speed V is set to be 1.5m/s (typical human walking speed [24]) or 10m/s (typical vehicle moving speed [25]). Note that vehicles can move faster than 10m/s but the results have the same trend and accuracy as those with a speed of 10m/s. To examine settings ranging from spare to dense networks, the radio range r_0 is varied from 1 to 40; hence the average node degree varies from 0 to 15. Various values of the active period have been simulated but only the results for $\tau = 100$ and 200 are shown, and results using other values of τ show a similar trend. Every point shown in the simulation result is the average value from 500 simulations. As the number of instances of random networks used in the simulation is large, the confidence interval is too small to be distinguishable and so is omitted in the figures.

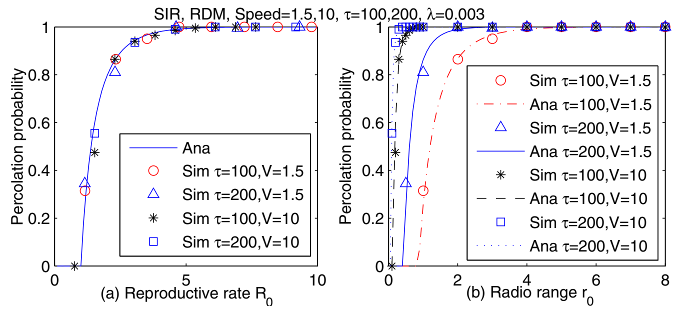

Fig. 4. The percolation probability, plotted in (a) versus the reproductive rate R_0 and in (b) versus the radio range r_0.

Fig. 4 shows the percolation probability as a function of R_0 and r_0. The simulation result shows the probability that at least x% of the nodes in the network receive the information sent from a source node, where the plots are almost the same for various values of x (e.g. 1, 5 or 10). The analytical result in Fig. 4 (a) is obtained using Corollary 2, where the analytical result in Fig. 4 (b) is obtained by substituting Eq. 1 into the result of Corollary 2. It can be seen from Fig. 4 (b) that as the radio range r_0, speed V or active period τ increases, the percolation probability increases correspondingly. This is because an increase in either the radio range r_0, node speed V or active period τ causes an increase in the number of nodes that come inside the radio range of an infectious node during its active period, hence improving the information propagation in the network. It is obvious that without a proper metric, it is difficult to characterize the percolation probability. It can be seen from Fig. 4 (a) that the curves plotted versus the reproductive rate R_0 converge together to the analytical result given by Corollary 2. This suggests that for different values of node speed, radio range or active period, but the same R_0, the percolation probability is the same. This is because the chosen metric, the reproductive rate R_0, fully captures the impact of radio range r_0, node density λ, node speed V and active period τ. It validates the claim that R_0 is a definitive metric for the percolation probability of a MANET.

Fig. 5 shows the steady state expected fraction of informed nodes as a function of R_0 and r_0. The analytical result in Fig. 5 (a) is obtained using Theorem 1, where the analytical result in Fig. 5 (b) is obtained by substituting Eq. 1 into

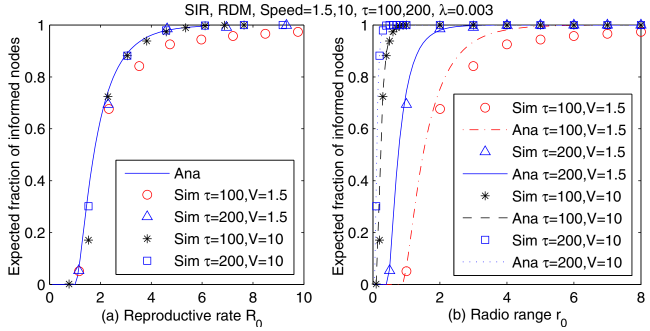

Fig. 5. Expected fraction of informed nodes z_0, plotted in (a) versus the reproductive rate R_0 and in (b) versus the radio range r_0.

the result of Theorem 1. It can be seen from Fig. 5 (b) that as the radio range r_0, speed V or active period τ increases, the expected fraction of informed nodes increases correspondingly.

The discrepancy between analytical result and simulation result shown in Fig. 5 is caused by the approximation made in using the upper bound of R_0. The impact of the discrepancy between the bound and the actual value, arising because the nodes that come into the radio range of an infectious node may not all be susceptible nodes, becomes more serious as time evolves and more nodes are infected. On the other hand, the problem is hardly notable at the beginning of the information propagation process. Hence the percolation probability shown in Fig. 4 is fairly accurate, because the study of the percolation probability only considers the probability that the information propagation process does not become extinct at the early stage.

Similarly to the discussion for Fig. 4, Fig. 5 (a) validates that the reproductive rate R_0 is a definitive metric for the expected fraction of informed nodes. We expect R_0 to be able to serve as a metric in the studies of other connectivity properties of MANETs, such as the information propagation speed, hop count statistics [12], etc.

VI. Conclusion and Future Work

In this paper, we study the propagation of a piece of information broadcast from a source node in a mobile ad-hoc network using the SIR epidemic routing algorithm. We proposed a metric, i.e. the expected number of susceptible nodes that have been inside an infectious node's radio range during the infectious node's active period, which is shown to be able to capture the impact of various parameters, including node density, mobility, radio range and length of the active period, on the information propagation process in a MANET. Further, analytical results are derived for the percolation probability and the expected fraction of informed nodes. The accuracy of the analytical results is verified using simulations. The research provides useful insights on the design of MANETs.

The analysis outlined in this paper can be extended to study the MANETs with other mobility models as well as other types of node distributions, which is one of our future work directions. Moreover, we are going to study the accuracy of our analysis using real world trace. Further, the information propagation speed in a MANET is of our interest.

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