On Information Dissemination in Infrastructure-based Mobile Ad-hoc Networks

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***Abstract*—In this paper, we consider 2D wireless multi-hop networks with mobile nodes randomly distributed on a torus, and a small number of base stations (infrastructure nodes) deterministically placed in the same area. Mobile nodes move following a random walk mobility model. A piece of information is broadcast from the base stations at the same time in a multi-hop manner using a Susceptible-Infectious-Recovered (SIR) epidemic routing algorithm. A distinguishing feature of the SIR algorithm, which leverages the mobility of mobile users, is that a relay node carries a piece of information for a pre-determined amount of time and forwards it at any available opportunity during that time. We provide analytical results for the percolation probability and for the expected fraction of nodes that receive the information when the information dissemination process stops. Further, we study the time delay of the information dissemination process. The accuracy of the analytical results is verified using simulations.**

***Index Terms*—mobile ad-hoc networks, infrastructure, percolation, random walk, epidemic routing**

I. Introduction

In this paper, we consider an infrastructure-based mobile ad-hoc network (MANET) with a large number of mobile nodes (MNs) moving following a random walk mobility model and a small number of base stations / infrastructure nodes (INs). Examples of such infrastructure-based MANETs include wildlife tracking sensor networks, vehicular ad-hoc networks and mobile social networks [1]. Taking the mobile social network as an example, the information (news or advertisement) 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 mobile users move and meet each other. This ad-hoc method of information dissemination can reduce the resource usage of base stations and lower the cost for service providers and users by utilizing cheaper radio resources, such as Bluetooth or cognitive radio, and physical mobility of the mobile users, for information dissemination. Moreover, in the case of natural disasters causing damage to or loss of a base station, ad-hoc communications between mobile devices may become crucial for survivors. In this paper, we investigate the information dissemination process in infrastructure-based MANETs.

The topology of a MANET often resembles 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. In view of this, epidemic routing algorithms [2] have been proposed as a fast and reliable approach to disseminate information in MANETs. An epidemic routing algorithm adopts the so-called *store-carry-forward* paradigm, where a mobile node stores and carries its received information and then forwards the information to its neighbors when 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 [3]. The epidemic routing algorithm leverages the mobility of nodes and efficiently disseminates information in MANETs [2], [4].

In this paper, we study the information dissemination process in a 2D infrastructure-based MANET, where a piece of information is broadcast from the infrastructure nodes to the mobile nodes in a multi-hop manner using a Susceptible-Infectious-Recovered (SIR) epidemic routing algorithm, which is introduced in detail in Section III. An asymptotic upper bound is derived for the percolation probability, viz. the probability that a non-vanishingly-small fraction of MNs receive the information as the number of MNs approaches infinity. Then we study the expected fraction of MNs that receive the information when the information dissemination process stops. Further, we derive a lower bound on the time delay of the information dissemination process. Finally, the accuracy of the analytical results is verified using simulations.

The rest of this paper is organized as follows: Section II reviews the related work. Section III introduces the network model and the epidemic routing algorithm considered in this paper. The analysis on the information dissemination process is given in Section IV. Section V validates the analysis using simulations. Finally Section VI concludes this paper and proposes possible future work.

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II. RELATED WORK

Some related work treating infrastructure-based ad-hoc networks can be found in the literature in the context of static networks. A static network is a special case of a MANET when the MNs are stationary, in which case the MNs are referred to as the ordinary nodes (ONs). Alternatively, a static network can be considered to be a snapshot of a MANET. In [5], Bermudez and Wicker considered a network where ONs are uniformly distributed in a unit square, with one IN at each corner of the square. They empirically investigated the fraction of ONs that are connected to at least one IN by Monte Carlo simulations. In [6], Zhang et al. considered a network with ONs Poissonly distributed and INs deterministically placed in a given 2D area. They studied the fraction of ONs which are connected to at least one IN in at most k hops. In [7], Dousse et al. considered a network where ONs are Poissonly distributed in $\Re^2$ and INs are placed on a grid. Using simulations, they showed that an increase in the number of INs provides little improvement on the probability that an arbitrary ON is connected to at least one IN, when the density of ONs is either very high or very low. However, the benefit of INs for the connectivity of networks with an intermediate density of ONs was not investigated. Note that all the above results are for static networks.

In view of the special characteristics of dynamic networks, epidemic routing algorithms [2], [4] have been proposed to disseminate information in MANETs. In [8], Zyba et al. studied the performance of a Susceptible-Infectious (SI) epidemic routing algorithm using real world mobility traces. By separating users into two behavioral classes, they obtained the successive meeting time of two nodes and the fraction of nodes that receive the information broadcast from an arbitrary source. In [9], Zhang et al. studied analytically the performance of SIR epidemic routing in a MANET where nodes are Poissonly distributed on a torus and move following a random direction model. They studied the fraction of MNs that receive the information broadcast from an arbitrary MN. However, the aforementioned studies considered only ad-hoc connection between MNs in a MANET without infrastructure support.

Time delay is an important metric for both end-to-end and broadcast information disseminations. In [10], Groenevelt et al. studied the end-to-end information dissemination in a MANET using an unrestricted multi-copy protocol like the SI epidemic routing algorithm. Using the approximation that the successive meeting time of two nodes follows an exponential distribution, they showed that the end-to-end delay between an arbitrary pair of nodes converges to $\frac{\log N}{0.57721N}$ asymptotically as the number of nodes $N \to \infty$. In [11], Zhang et al. studied the performance of several epidemic routing algorithms in MANETs assuming that the successive meeting time of two nodes follows an exponential distribution with rate β. By solving ordinary differential equations, they showed a similar result to that in [10], i.e. the expected end-to-end delay between an arbitrary pair of nodes is $\frac{\log N}{\beta N}$ using the SI epidemic routing algorithm, where N is the number of nodes in the network. In [12], Zhou et al. studied the performance of SI epidemic routing in a MANET with N mobile nodes and M base stations. At each time slot, a single pair of transmitter-receiver nodes is uniformly and randomly selected among $N+M$ nodes in the network. It follows that the rate of transmission is once per time slot, irrespective of the number of MNs in the network. Modeling the information propagation process by a Markov chain, they found that the expected time required to deliver a message from an arbitrary MN to at least one of the base stations is $\Theta(N \log N)$. The analysis in this paper is not based on the assumption on the inter-meeting time or the rate of transmission. Further, we show the impact of various parameters, i.e. node density, radio range and a quality-of-service metric (fraction of nodes that receive the information), on the delay of the information dissemination in an infrastructure-based MANET.

III. SYSTEM MODEL

A. Network model

Consider a MANET where mobile nodes (MNs) are randomly and independently distributed on a torus $(0, L]^2$ [13] following a homogeneous Poisson point process with intensity λ. It follows that the expected number of MNs in the network is $N = \lambda L^2$. Further, M infrastructure nodes (INs) are deterministically placed in the same area, in a way that they are not clustered together, as shown in Fig. 1. An example is to place the INs in a way that the associated Voronoi cells of these INs have equal size. We consider that the number of INs is much less than the number of MNs, i.e. $M \ll N$, which reflects the fact that INs are usually more expensive. Two nodes are directly connected iff (if and only if) their Euclidean distance is smaller than or equal to the radio range r_0, viz. we adopt the unit disk communication model. The use of torus allows a node located near the boundary to have the same number of connections probabilistically as a node located near the center. Therefore, the torus topology is a simplification that helps to obtain analytical results, because there is no need to consider the boundary effect, and it is commonly used in this area [10], [13].

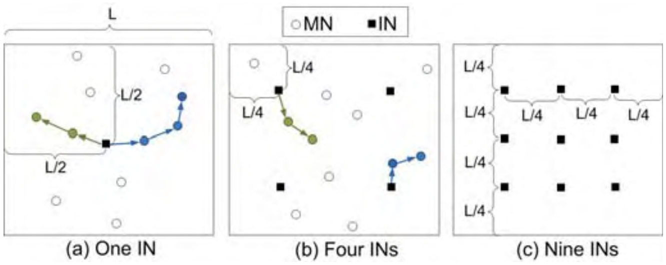

Fig. 1. Examples of the deployment of one, four or nine infrastructure nodes.

Further, MNs move according to the random walk model (RWM) [14], following which each MN moves at a constant speed V in a particular direction for a time duration following an exponential distribution with mean ζ seconds. The direction is uniformly chosen in $[0, 2\pi)$, independent of the direction of other MNs and the node's direction in other time intervals.

Note that when $\zeta \to \infty$, i.e. the direction does not change over time, and our analysis therefore provides the results for a MANET with the random direction model (RDM) [14]; when $\zeta \to 0$ the mobility model is like Brownian motion; when $V \to 0$, our analysis provides the results for a static network.

It is worth noting that under the aforementioned node distribution model and mobility models, the spatial distribution of the MNs is stationary and always follows a homogeneous Poisson point process with intensity λ at any time instant [15].

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

Consider a basic stochastic SIR epidemic routing algorithm [9], [16], where a piece of information is broadcast from the INs to the MNs at time $t = 0$. We consider that the INs are connected to each other by a backbone network so that INs can broadcast the same piece of information at the same time.

By analogy to the way a disease spreads in a human network, a MN can be in any of three states S, I, R: A MN that has never received the information from any of the INs is in the state of susceptible (S), in which the MN can accept incoming transmissions if such opportunity arises. A susceptible node transits into the state of infected and infectious (I) immediately after it has received a copy of the information. A node in state I keeps transmitting the information, i.e. remains infectious, for a certain time period τ, which is referred to as the *active period*. Note that τ is a pre-determined value which is the same for all nodes. After the active period, the node enters into the state of recovered and immune (R). A node in state R stops transmitting the information to other nodes and will ignore all future transmissions of the same information from other nodes. An animation of the information dissemination process in a MANET is available on [17].

Note that the INs only transmit a piece of information for a time period of length τ, after which the information propagates in the network using the epidemic routing algorithm. The information dissemination naturally stops (i.e. reaches the *steady state*) when there is no infectious node in the network. We study the fraction of informed MNs when the information dissemination process has reached the steady state, where the *informed MNs* are MNs that have received the information.

The network introduced in this subsection is denoted by $\mathcal{G}(L, \lambda, M, V, \zeta, \tau)$ hereafter. Further, we consider that the network is deployed on a sufficiently large torus (i.e. $L > V\tau$) such that within the active period τ, a node will not be wrapped back to the point where it starts moving at time 0.

IV. Analysis of the information dissemination process

A. The definitive metric

The information dissemination process of a MANET is determined by a number of parameters such as node density, mobility, radio range and the length of active period. In this subsection, a single metric is proposed, which captures the impact of the above parameters.

Definition 1. The *effective node degree* R_0 of an infectious node is the expected number of MNs that have been inside an infectious node's radio range during the infectious node's active period.

Note that R_0 is the same for all MNs because of the stationarity and homogeneity of node distribution on the torus. Further, we do not need to consider the INs in the calculation of R_0, because the INs are the sources of the information and they do not act as a relay which receives an information then re-broadcast it. Next we provide an upper bound on R_0.

Lemma 1. *Consider a network $\mathcal{G}(L, \lambda, M, V, \zeta, \tau)$. The effective node degree R_0 satisfies:*

$$R_0 \le \frac{8r_0 V\lambda\tau}{\pi} + \pi r_0^2 \lambda \tag{1}$$

Proof: We first study the size of the area covered by the radio range of a typical mobile node (Q) during its active period assuming that its direction does not change. As shown in Fig. 2, the area consists of two parts. The first part is the area swept by a segment of length $2r_0$ perpendicular to the trajectory of the node, which is shown by the line-shaded area and is referred to as the *area swept by the radio range*. The second part is the area of two half-circles, which is shown by the uniformly shaded area and whose size is πr_0^2.

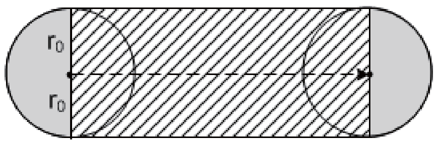

Fig. 2. An illustration of the area (line-shaded and uniformly shaded) covered by the radio range of a node when the node moves along a straight line.

Note that if a MN changes its direction over time, then this will cause overlapping of the trajectory and a reduction in the size of the area swept by the radio range during its active period. However, an analytical upper bound on this area, call it $\tilde{A}(V)$, can be obtained by ignoring the reduction of the area caused by the overlapping of the trajectory. It is straightforward that $\tilde{A}(V) \le 2r_0 V\tau$.

Denote by Θ the angle measured counterclockwise from the direction of the node Q to the direction of an arbitrary MN. Recall that the direction of an arbitrary MN is randomly and uniformly chosen in $[0, 2\pi)$, independent of the directions of other nodes. It can be shown that Θ is uniformly distributed in $[0, 2\pi)$. Based on the thinning property of a Poisson process, it can be shown that the subset of MNs moving toward directions $\Theta \in (\theta, \theta + d\theta)$ follows a homogeneous Poisson process with intensity $\lambda d\theta$. Further, the relative speed between node Q and the aforementioned subset of MNs is $\sqrt{V^2 + V^2 - 2V^2 \cos\theta} = 2V|\sin\frac{\theta}{2}|$. To facilitate the analysis, we consider a new coordinate system where the origin is set at an arbitrary node moving toward direction θ. In this new coordinate system, the locations of the aforementioned subset of MNs are approximately stationary[1] and the node

[1]The locations of the MNs may have small displacements during time interval τ due to a small direction difference $d\theta$. However the displacements become vanishingly small when $d\theta \to 0$ while V and τ are finite.

Q is moving at speed $2V|\sin\frac{\theta}{2}|$. It follows that in the new coordinate system, the expected size of area swept by the radio range of node Q is $\tilde{A}(2V|\sin\frac{\theta}{2}|)$. Therefore the expected number of MNs moving toward directions $\Theta \in (\theta, \theta + d\theta)$, that have been inside the area swept by the radio range of node Q during its active period, is $\tilde{A}(2V|\sin\frac{\theta}{2}|)d\lambda\theta$.

Considering all mobile nodes in the network, it is straightforward that the expected number of MNs that have been inside the area swept by the radio range of node Q is:

$$\int_0^{2\pi} \tilde{A}(2V|\sin\frac{\theta}{2}|)\frac{1}{2\pi}\lambda d\theta \quad (2)$$

$$\leq \int_0^{2\pi} 2r_0 2V|\sin\frac{\theta}{2}|\tau\frac{1}{2\pi}\lambda d\theta \quad (3)$$

$$= \frac{2r_0V\tau\lambda}{\pi}\int_0^{2\pi}|\sin\frac{\theta}{2}|d\theta = \frac{8r_0V\tau\lambda}{\pi} \quad (4)$$

Therefore, the expected number of nodes that have been inside the radio range of node S during its active period is $R_0 \leq \frac{8r_0V\tau\lambda}{\pi} + \pi r_0^2\lambda$. ■

B. Percolation probability

In this subsection, we study the percolation probability of an infrastructure-based MANET in the limit of large network size, 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, such as λ, V and r_0, constant. Note that the distance between INs also increases with L such that the ratio between the two values is kept constant as shown in Fig. 1. The percolation probability is defined in the following:

Definition 2. The *percolation probability* p_c of an infrastructure-based MANET is the probability that a piece of information broadcast from the INs is received by a *non-vanishingly-small* fraction of MNs in the steady state, in the limit of large network size.

We have the following result for the percolation probability.

Theorem 1. *Consider a network $\mathcal{G}(L, \lambda, M, V, \zeta, \tau)$, whose effective node degree is known to be R_0. The percolation probability is $p_c \leq 1 - (\frac{W(-R_0e^{-R_0})}{-R_0})^M$, where $W(.)$ is the Lambert W Function.*

Proof: We first consider the information dissemination process of a single IN, in which a node (say A) is a *child* of another node (say B) iff node A (which must be a susceptible node) receives the information from node B (which must be an infectious node). Denote by $\chi_N^1(k)$ the number of nodes at the k^{th} generation in the information dissemination process of a single IN. Then $\chi_N^1(k)$ can be modeled by a branching process whose expected number of children per node is smaller than R_0, because of the reduction of the fraction of susceptible nodes in the network as the information propagates. Next we introduce a Galton-Watson branching process [18], in which the expected number of children per node is R_0. Denoted by $\chi^1(k)$ the number of individuals at the k^{th} generation of the Galton-Watson branching process. As discussed earlier, we have $\chi_N^1(k) \leq \chi^1(k)$ in stochastic ordering[2] for all $k \geq 1$. Note that at the first generation, though there is no previous reduction of the fraction of susceptible nodes, the relation $\chi_N^1(1) \leq \chi^1(1)$ is still valid because an IN does not move over time so that the expected number of children of an IN can be smaller than R_0.

Define $q = \Pr(\lim_{k\to\infty}\chi^1(k) \to 0)$ to be the *extinction probability* of the Galton-Watson branching process $\chi^1(k)$. It can been shown (cf. [18, Theorem 6.5.1]) that $q = \frac{W(-R_0e^{-R_0})}{-R_0}$, where $W(.)$ is the Lambert W Function [19]. Further, define $q_N = \Pr(\lim_{k\to\infty}\chi_N^1(k) \to 0)$ to be the extinction probability of the branching process $\chi_N^1(k)$. Due to the stochastic ordering $\chi_N^1(k) \leq \chi^1(k)$, we have

$$q_N \geq q = \frac{W(-R_0e^{-R_0})}{-R_0} \quad (5)$$

Recall that we have M INs in the network. Denote by p_c' the probability that at least one of the M information dissemination processes, rooted at M INs respectively, does not become extinct. It can be shown that

$$p_c' \leq 1 - q_N^M \leq 1 - q^M \quad (6)$$

where the second inequality is due to Eq. 5 and the first inequality is due a spatial correlation between INs. The *spatial correlation between INs* arises if the Euclidean distance between two INs is small, for then two information dissemination processes may share a common set of susceptible nodes. As the information propagates, the reduction of the fraction of susceptible nodes caused by the information dissemination process of one IN can reduce the expected number of children per node in the information dissemination process of another IN. Therefore we have $p_c' \leq 1 - q_N^M$.

Further, the event of having an unbounded number of informed MNs in the limit of large network size (whose probability is p_c') is a necessary condition for having a non-vanishingly-small fraction of MNs in the limit of large network size. Therefore we have $p_c \leq p_c'$. ■

Remark 1. To improve the percolation probability of a given network $\mathcal{G}(L, \lambda, M, V, \zeta, \tau)$, one can reduce the spatial correlation between INs by reducing the number of susceptible nodes shared by the INs. Therefore we consider placing the INs in a way that the associated Voronoi cells have equal size, as introduced in Section III.

Remark 2. The above results suggest that an increase in the number of INs provides little improvement on the percolation probability when the density of MNs is either very low (such that $q = 1$) or very high (such that $q = 0$). This result coincides with the result for a static network [7]. However, our results further suggest that when the density of MNs is intermediate, an increase in the number of INs can improve the percolation probability significantly, which is further verified in Section V.

In addition, it can be shown that $1 - (\frac{W(-R_0e^{-R_0})}{-R_0})^M$ is 0 for $0 < R_0 \leq 1$ and it is monotonically increasing with

[2]Using stochastic ordering, we say $\chi_N^1(k) \leq \chi^1(k)$ iff $\Pr(\chi_N^1(k) > a) \leq \Pr(\chi^1(k) > a)$ for any number a.

respect to R_0 for $R_0 > 1$. Therefore the following corollary can be readily obtained using Lemma 1 and Theorem 1.

Corollary 2. *Consider a network $\mathcal{G}(L, \lambda, M, V, \zeta, \tau)$. The percolation probability is*

$$p_c \leq 1 - (\frac{W(-(\frac{8r_0V\lambda\tau}{\pi} + \pi r_0^2\lambda)e^{-\frac{8r_0V\lambda\tau}{\pi} - \pi r_0^2\lambda})}{-\frac{8r_0V\lambda\tau}{\pi} - \pi r_0^2\lambda})^M$$

where $W(.)$ is the Lambert W Function.

The percolation probability provides the probability that a piece of information can be spread out to a significant fraction of MNs. In the next subsection, we quantify how many MNs can receive the information.

C. Expected fraction of informed MNs

Recall that a piece of information broadcast from INs is said to percolate if the information is received by a non-vanishingly-small fraction of MNs in the steady state.

Define z_p to be the expected fraction of informed MNs in the steady state given that the information percolates. Because $M \ll N$, the following result can be readily obtained based on Lemma 3 in [9].

Theorem 2. *Consider a network $\mathcal{G}(L, \lambda, M, V, \zeta, \tau)$, whose effective node degree is known to be R_0. If the information percolates, then the expected fraction of informed MNs in the steady state satisfies $z_p \leq 1 + \frac{1}{R_0}W(-R_0e^{-R_0})$, where $W(.)$ is the Lambert W Function.*

It is further shown in Section V that increasing the number of INs has little impact on z_p. On the other hand, increasing the number of INs can reduce the delay of the information dissemination process, which is studied in the next subsection.

D. Information dissemination delay

Consider that a piece of information is broadcast from the INs at time $t = 0$ using the SIR epidemic routing algorithm. Let $T(z)$ be the expected time when the fraction of informed MNs reaches z, for $0 < z < 1$. In this subsection, we provide a lower bound on the delay $T(z)$ by considering a SI in lieu of SIR epidemic routing algorithm.

It is worth noting that in a multi-hop network, a piece of information can be forwarded several hops in a short time interval if a journey exists in such time interval. The multi-hop forwarding is usually much faster than the store-carry-forward method because the latter method relies on the physical movement of MNs. Therefore the time delay of the information dissemination process allowing multi-hop forwarding is different and more realistic than that in the previous research of epidemics or MANETs based on a particular inter-meeting time or rate of transmission [11], [12], [16], as discussed in Section II. We take the multi-hop forwarding into consideration and provide the following result.

Theorem 3. *Consider a network $\mathcal{G}(L, \lambda, M, V, \zeta, \tau)$. A piece of information is broadcast from the INs at time $t = 0$ using the SIR epidemic routing algorithm. Let $T(z)$ be the expected time when the fraction of informed MNs reaches z, for $0 < z < 1$. Then $T(z) \geq \frac{\tau}{R_0 + Nz_s} \ln \frac{(zN/M) - z}{1 - z}$, where $z_s = (1 + \frac{1}{\lambda\pi r_0^2}W(-\lambda\pi r_0^2 e^{-\lambda\pi r_0^2}))^2$ and $N = \lambda L^2$.*

Proof: Firstly we consider the multi-hop forwarding. Let z_m be the expected fraction of MNs that receive the information broadcast from an arbitrary node at an arbitrary time instant. By letting $V = 0$, Lemma 1 gives $R_0 \leq \lambda\pi r_0^2$. Then using Corollary 2 and Theorem 2, it can be shown that $z_m \leq (1 + \frac{1}{\lambda\pi r_0^2}W(-\lambda\pi r_0^2 e^{-\lambda\pi r_0^2}))^2 \triangleq z_s$.

It is straightforward that the recovery mechanism reduces the number of infectious nodes hence slows down the information dissemination process. Therefore we can obtain a lower bound on $T(z)$ by ignoring the recovery mechanism: viz. considering a SI epidemic spreading where the expected number of nodes that come into the radio range of an arbitrary infectious node in a unit time interval is $\alpha = \frac{R_0 + Nz_s}{\tau}$. Let $I(t)$ be the number of infectious nodes at time t, then it can be shown using the same method as that in Lemma 3 of [9]:

$$I'(t) = \alpha(1 - \frac{I(t)}{N})I(t) \tag{7}$$

Solving the above ODE, we have:

$$I(t) = \frac{\alpha \exp(C_1 + \alpha t)}{\frac{\alpha}{N}\exp(C_1 + \alpha t) + 1} \tag{8}$$

Because $I(0) = M$, we have $\exp(C_1) = \frac{1}{\alpha/M - \alpha/N}$. Then:

$$I(t) = \frac{\alpha \exp(\alpha t)}{\frac{\alpha}{N}\exp(\alpha t) + (\alpha/M - \alpha/N)} \tag{9}$$

$$= \frac{N}{1 + (N/M - 1)\exp(-\frac{R_0 + Nz_s}{\tau}t)} \tag{10}$$

Letting $z = \frac{I(t)}{N}$, the above equation can be re-written as:

$$t(z) = \frac{\tau}{R_0 + Nz_s} \ln \frac{\frac{N}{M}z - z}{1 - z} \tag{11}$$

As discussed earlier, we have $T(z) \geq t(z)$. ∎

Note that Theorem 3 can serve as a lower bound for other information dissemination methods for infrastructure-based MANETs, because the SI epidemic routing algorithm, like flooding, has been shown to have the lowest delay for information dissemination in MANETs [4], [10], [11].

V. Simulation Results

In this section, we report on simulations to verify the accuracy of the analytical results. The simulations are conducted using a MANET simulator written in C++. MNs are deployed on a torus $(0, 800]^2$ following a homogeneous Poisson process with intensity $\lambda = 0.002$ users/m^2, which is the population density in Sydney city [20]. Speed V is 1.5m/s (typical human walking speed [21]) or 10m/s (typical vehicle moving speed [22]). The radio range r_0 is varied from 1 to 20. (The radio range of a Bluetooth device is around 10m [23].) The active period τ is set to be 100 or 200, where results using other values of τ show a similar trend. The INs are placed deterministically as shown in Fig. 1 and it remains our future work to find the optimal placement of INs for the information dissemination in MANETs. Every point shown in the figures is the average value from 500 simulations, where the confidence interval is too small to be distinguishable and so is omitted.

In Fig. 3, the simulation result for percolation probability shows the probability that at least 5% of MNs receive the information broadcast from INs. Firstly, it can be seen in Fig. 3 that the analytical result well captures the impact of various parameters, e.g. nodal speed, radio range and the number of INs on the information dissemination process. Further, it can be seen in Fig. 3 (a) that a significant higher percolation probability can be achieved by a small number of additional INs (e.g. from 1 IN to 4 INs). On the other hand, it can be seen in Fig. 3 (b) that the introduction of more INs cannot improve the expected fraction of informed nodes in the steady state if the information percolates. This observation confirms our assertion given in Section IV-C. Further study reveals that if a MN (or a group of MNs) does not receive the information given that the information percolates elsewhere in the network, the MN (or the group of MNs) is usually geometrically separated from the informed nodes. However, a small number of additional INs has a small probability of bridging the geometric gap.

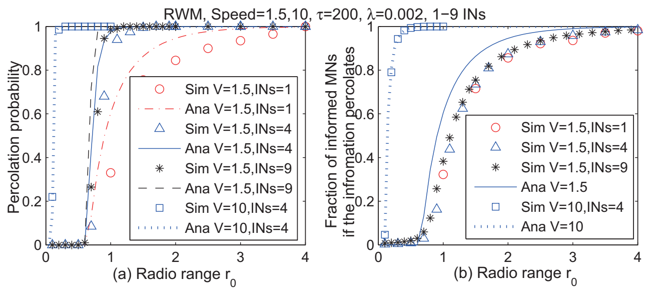

Fig. 3. Analytical (Ana) and simulation (Sim) results for (a) Percolation probability; (b) Expected fraction of informed MNs if the information percolates.

Fig. 4 shows the time delay for a piece of information to be received by 50% of MNs. It can be seen that our analytical result captures the impact on the delay of network parameters such as radio range, nodal speed or the number of INs.

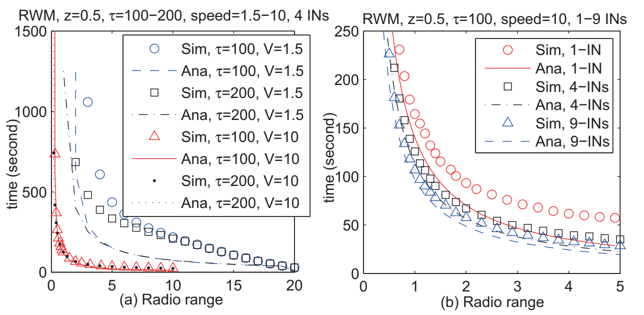

Fig. 4. Analytical (Ana) and simulation (Sim) results for the time delay for a piece of information to be received by 50% of MNs. The curves for V=10 overlap in (a), but the accuracy of the results for V=10 can be seen in (b).

VI. Conclusions and Future Work

In this paper, we study the dissemination of a piece of information broadcast from INs in an infrastructure-based MANET using a SIR epidemic routing algorithm. Analytical results are derived for the percolation probability, the expected fraction of informed MNs and the time delay. The accuracy of the analytical results is verified using simulations. In the future, we intend to study an infrastructure-based MANET driven by a real world trace.

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