Edge-Markovian Dynamic Graph Based Performance Evaluation for Delay Tolerant Networks

Li Qiu*, Yong Li*, Pan Hui†, Depeng Jin*, Li Su*, Lieguang Zeng*
*Department of Electronic Engineering, Tsinghua University, Beijing 100084, China.
†Deutsche Telekom Laboratories/TU-Berlin, Ernst-Reuter-Platz 7, Berlin 10587, Germany.
Email: jindp@mail.tsinghua.edu.cn

***Abstract*—Groups of people with mobile phones using short range connections like WiFi and Bluetooth to propagate messages can be modeled as, with regard to regular absence of end-to-end connection, Delay Tolerant Networks (DTNs). The study of message transmission speed in such kind of networks has attracted increasing attention in recent years. In this paper, we present a realistic framework to model the message propagation process, and give a detailed expression of average information dissemination delay based on message size, users' selfishness, number of involved subscribers and other related parameters. We apply our model to real-life traces to assess its reliability by comparing the theoretical results with measured statistics, and present extensive upshots to evaluate the influence of various parameters on system performance.**

I. Introduction

With the increasing use of smart mobile devices which offer ubiquitous Internet access and diverse multimedia authoring, mobile traffic is growing at a fantastic speed. Many researchers from networking and financial sectors predict that by 2014, broadband mobile users' average traffic consumption will be 7GB which is 5.4 times more than the consumption of users nowadays and the total mobile data traffic throughout the world will be 39 times larger [1]. Using mobile phones with short range connections to help with propagating the mobile traffic is one of the solutions to the explosive traffic growth problem.

Delay Tolerant Networks (DTNs) offer valuable insights into this study of message propagation process, as they take the general lack of end-to-end path property into consideration, which is caused by sparse node density and unpredictable node mobility. The store-carry-forward strategy [2] has been utilized in such kind of network by allowing nodes to store the message before passing it on to the next node. Numerous works have taken advantage of DTNs to set up their own models under various conditions, including: vehicular ad hoc networks [3], deep-space interplanetary networks [4], underwater networks [5], military networks [6], *etc.*

Yet, to study DTNs' various characters, while challenging, is still a meaningful task. Some of the fascinating characters involve: the relationship of message size and transmission delay, what impacts an increasing number of nodes brings about when infecting ratio is definite, whether making all people willing to transmit the information could significantly shorten the message dissemination delay and so on. Thorough discussions of above questions would offer great help for efficiently transmitting information within a short time at lowest cost.

Some related work has already been done in this realm. Early works commonly focused on evaluating the performance of epidemic routing schemes by using simulation which inevitably endowed their research confined to a limited aspect without regarding the influence of various parameters [7]. More recently, several models based on edge-Markovian dynamic graphs have been proposed to compute the average dissemination delay or successful transmission probability [2][8][9]. However, these papers either ignored the impact of nodes' social selfishness or based on the simple assumption that connectivity graph evolves in discrete time. Moreover, all of them failed to capture an important correlation between dissemination delay and message size.

We propose a more actual model by taking realistic properties into consideration. Unlike recent works [10][11], we apply exponential distribution both to contact and inter-contact periods to quantify the impact of message size as larger messages usually require longer contact period to propagate. We also consider other social characters including distinct inter-contact periods, as various people might exhibit totally different behaviors owning to their working, living place and friends circle. Thus they should be divided into different groups according to their communication intervals with each other. On the other hand, sometimes people would be unwilling to forward a message to others due to energy and storage constrain or prefer to forward information to people in the same group with them. Such two kinds of activities are called individual selfishness and social selfishness respectively [12]. In our model, we concentrate on social selfishness which has a considerable effect on communication between groups. We compare our theoretical insights to results obtained from two real traces, RWP in the ONE simulator and Reality from the Reality Project of MIT. Finally, we quantify the influence of the number of nodes on the system performance (*i.e.* assess the parameter' influence on average dissemination delay in this paper) to find whether they would help in the message propagation strategy design.

II. Related Work

In the past decade, lots of people have contributed to the study of message propagation process. Vahdat $et\ al.$ [13] first introduced the concept of epidemic routing where random pair-wise exchanges of messages among mobile hosts ensure eventual message delivery. Juang $et\ al.$ [7] distributed custom tracking collars on animals across a wild area trying to use the least energy, storage, and other resources necessary to maintain a reliable system. Later Fall proposed the DTN model to study the networks that lack continuous connectivity, which has been widely used ever since [5]. Shortly after that, Markovian models were exploited to evaluate the performance of epidemic routing [14][15][16]. Chaintreau $et\ al.$ [17] used simple sequences of uniform random graphs for modeling random temporal graphs to analyze the diameter of opportunistic mobile networks. Groenevelt $et\ al.$ [15] proposed a stochastic model based on the number of nodes and the parameter of an exponential distribution to estimate message delay accompanied with comparison of analytical results to simulation results obtained from three different mobility models. By using ordinary differential equations (ODE), Zhang $et\ al.$ [2] investigated how resources such as buffer space and the number of copies made for a packet can be traded for faster delivery. More recently, Li $et\ al.$ [12] defined a metric of selfish factor to evaluate the impact of social selfishness in DTNs.

Clementi $et\ al.$ gave theoretical upper and lower bound for flooding time ($i.e.$ completion time of the flooding mechanism aiming to broadcast a piece of information from a source node to all nodes) by dividing the flooding process into distinct phases [9]. They proved that after $t = O(\frac{\log n}{\log(1+np)})$ time steps, the number of informed nodes was at least βn with high probability by Chernoffs bound, and then after $O(\frac{\log n}{\log np})$ time steps with high probability all the nodes would be infected, where n represents the number of nodes and p stands for edge-birth rate. Compared to their work, we offer explicit results for average dissemination delay rather than vague upper and lower bound barely useful under the condition of numerous nodes. In addition, our model takes various social characters into consideration and can be used to calculate the situation when only a part of nodes need to be infected.

On the assumption that connectivity graph evolves in discrete time, Whitbeck $et\ al.$ [8] exploited state transition matrix to calculate the rate of successfully infecting a certain destination node within a limited period of time upon various bundle sizes. They gave accurate estimation for successfully transferring probability for $\alpha \leq 1$ ($i.e.$ bundle size), an upper and lower bound for $\alpha > 1$ and then compared theoretical results with measured data obtained from Rollernet Trace. Unlike their work, we present average dissemination delay rather than successful transmission rate. Moreover, Our premise of continuous evolving connection graph is more justifiable than their discretely evolving graphs assumption. The starting point of our work is [11], which presented a method to calculate the dissemination delay without regard to message size and infecting ratio. In this paper, we set up an integrated model that could be used to quantify various parameters' effect on the transition delay as well as applied to real-life trace.

III. System Model

Due to nodes' distinct location properties and professional affiliation in DTNs, they should be divided into various non-overlapping groups. However, discussing such a complex situation is far from easy, as we have to pay attention to the number of infected nodes in each group. In this paper, we mostly focus on two-group case which can easily be extended to multiple-group case.

A. Communities

We divide all the nodes in the network into two communities A and B. Nodes in the same group are more likely to set up a connection than across distinct groups which means a longer geographical distance and less probability of meeting each other. We assume there are N nodes in A, M nodes in B, and a node in A gets the original message initially. Our main purpose is to model the single message's propagation process in these two communities.

B. Link Generating and Perishing Model

All links joining every two nodes in the network have contact and inter-contact periods, and transmission of the message can only occur in contact period of a link which connects an infected and an uninfected node. We assume every contact period as well as inter-contact period follows an exponential distribution with intensity μ and λ respectively, which is widely used in modeling opportunistic DTNs [18]. We define intra-group link generating (perishing) speed as λ_1 (μ_1) and inter-group link generating (perishing) speed as λ_2 (μ_2). Usually λ_1 is larger than λ_2.

C. Bundle Size

A small message can always be transmitted once a link comes into existence. However, in a realistic DTN, it can be a different case with regard to diverse message sizes. To be more specific, propagating text information could always be finished before deadline, while infecting another node with a video is seldom completed within one contact period. We assume that all links, when up, have equal capacity and once the message is not successfully sent, next time the transmission will still restart from the scratch. We refer to α, which represents the time needed to transmit a message as its bundle size. According to exponential law's character, the probability of a contact period being greater than α can be calculated by the following integral:

$$\int_{\alpha}^{+\infty} \mu e^{-\mu t} dt = e^{-\mu\alpha} \tag{1}$$

.

Therefore, on average a message with size α is transmitted with probability $e^{-\mu\alpha}$ through that link once it comes into existence. In other words, after a link has been connected for $1/e^{-\mu\alpha}$ times, the message has a high probability of being transmitted. It thus could be interpreted as the link generating speed decreases to $\lambda e^{-\mu\alpha}$, or $\lambda_1 e^{-\mu_1\alpha}$ for intra-group link generating speed and $\lambda_2 e^{-\mu_2\alpha}$ for inter-group link generating speed.

D. Social Selfishness

When social selfishness is taken into consideration, it will undoubtedly affect the message propagating rate [12]. We assume on average the intra-group and inter-group probability of people willing to forward a message is p_1 and p_2 respectively. Consequently, the intra-group link generating speed changes to $p_1\lambda_1 e^{-\mu_1\alpha}$ while the inter-group link generating speed changes to $p_2\lambda_2 e^{-\mu_2\alpha}$.

IV. Achieving Dissemination Delay

Unlike previous works which mostly concentrate on forwarding a message to a single destination, we are interested in the average delay for a portion of nodes in A being infected. We refer to r $(0 < r < 1)$ as the percentage of nodes required to infect. Assuming i stands for the number of nodes being infected in A and j for B. As present state relies only on previous state, the nodes in both A and B as well as all the the links make up an edge-Markovian dynamic graph. The Markov chain has the following $(\lceil rN \rceil - 1)(M+1)+1$ distinct states:

(1) States (i,j): $1 \le i \le \lceil rN \rceil - 1$ and $0 \le j \le M$, these states are transient.

(2) State $Succ$: this is an absorbing state which indicates at least rN nodes in A are infected.

We define $P_{i,j\to succ}$ as the probability of transition from the state (i,j) to the state $Succ$; define $P_{i,j\to i',j'}$ as the transition probability from state (i,j) to (i',j'). While such two probabilities vary according to the intermediate time t, when t is relatively small, they are also functions of the following primitives. Given two sets of nodes U and W, if every node in U is able to infect each node in W with probability p, then the odds that m nodes in W will be infected is computed as follows [8]:

$$P_{\inf}(m,p,|U|,|W|) = C_{|W|}^{m}(1-p)^{|U|(|W|-m)}(1-(1-p)^{|U|})^{m}. \quad (2)$$

Thus, we can get

$$\begin{aligned} P_{i,j\to succ} = &\sum_{n=\lceil rN \rceil}^{N}\sum_{m=0}^{n-i} P_{\inf}(m, p_1\lambda_1 e^{-\mu_1\alpha}t, i, N-i) \\ &\times P_{\inf}(n-i-m, p_2\lambda_2 e^{-\mu_2\alpha}t, j, N-i-m) \end{aligned} \quad (3)$$

$$\begin{aligned} P_{i,j\to i',j'} = &\sum_{m=0}^{i'-i}\sum_{n=0}^{j'-j} P_{\inf}(m, p_1\lambda_1 e^{-\mu_1\alpha}t, i, N-i) \\ &\times P_{\inf}(i'-i-m, p_2\lambda_2 e^{-\mu_2\alpha}t, j, N-i-m) \\ &\times P_{\inf}(j'-j-n, p_2\lambda_2 e^{-\mu_2\alpha}t, i, M-j-n) \\ &\times P_{\inf}(n, \lambda_1 e^{-\mu_1\alpha}, j, M-j) \end{aligned} \quad (4)$$

According to the definition of continuous Markov chain, every element of transition rate matrix Q is associated with

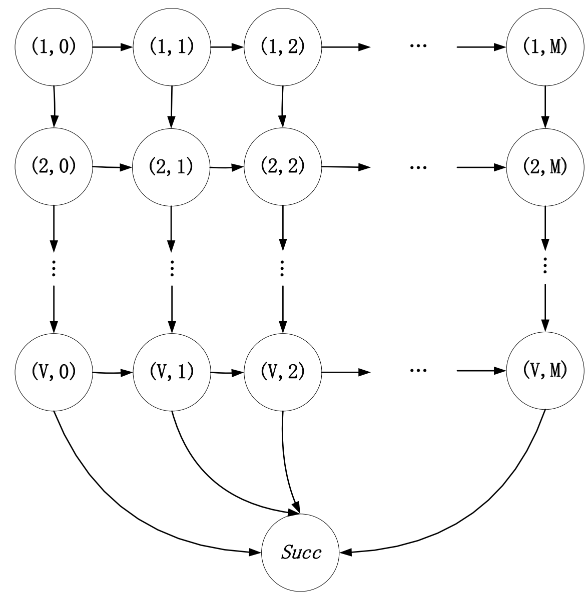


Fig. 1. The transition of every involved state in Markov chain.

transferring probability p as exhibits:

$$\begin{aligned} q_{i,j\to i,j} &= -\lim_{t\to 0}\frac{1-p_{i,j\to i,j}(t)}{t}, \\ q_{i,j\to i'j'} &= \lim_{t\to 0}\frac{p_{i,j\to i'j'}(t)}{t}(i \ne i' or j \ne j'), \end{aligned} \quad (5)$$

where element $q_{i,j\to i',j'}$ represents the transferring speed from state (i,j) to state (i',j'), $q_{i,j\to i,j}$ is derived from the negative sum of every other element in the same row, while the state in front of the arrow stands for the row and the state after the arrow stands for the column of Q.

We define $V = \lceil rN \rceil - 1$, $K = V(M+1)$, Q could also be divided into several sub-matrixes in the following form:

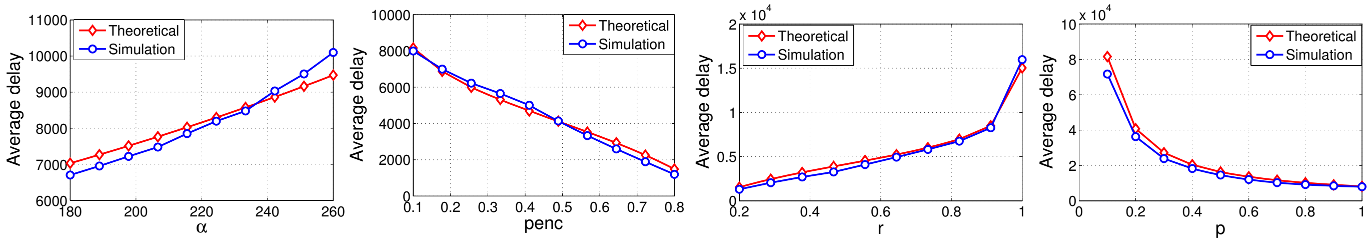
$$Q = \begin{bmatrix} T & R \\ 0 & 0 \end{bmatrix},$$

where T is a $K \times K$ matrix, R is a $K \times 1$ matrix denoting the transition rate from transient state (i,j) to absorbing state $Succ$. The all-zero $1 \times K$ matrix in the left results from the fact that absorbing state $Succ$ will never migrate to a transient state, whereas the element 0 on the right side is attributed to the negative sum of every single element of the left all-zero vector. Based on the above upshots, we could acquire every element of T as follows:

$$\begin{aligned} t_{((i,j),(i,j))} &= -(\lambda_1 i + \lambda_2 j)(N-i) - (\lambda_1 j + \lambda_2 i)(M-j), \\ &\qquad (1 \le i \le V, 0 \le j \le M), \\ t_{((i,j),(i+1,j))} &= (N-i)(j\lambda_2 + i\lambda_1), (1 \le i \le V-1, 0 \le j \le M), \\ t_{((i,j),(i,j+1))} &= (M-j)(j\lambda_1 + i\lambda_2), (1 \le i \le V, 0 \le j \le M-1), \end{aligned} \quad (6)$$

where λ_k is an abbreviation for $p_k\lambda_k e^{-\mu_k\alpha}$ $(k = 1,2)$, and all the other elements in the matrix are zero. According to T and Q, the transition relationship of every involved state is shown in Fig. 1.

Denote $G_D(t)$ as the probability that the Markov chain does not arrive at absorbing state from initial state (1,0) at time t, then the average delay (the average time to get to



(a) Message size (b) Initially infected percentage (c) Infecting ratio (d) Transmission Willingness

Fig. 2. The theoretical result and measured dissemination delay upon various parameters in RWP. When unspecified, $\lambda = 6.1083e-6$, $\mu = 0.0037$, $N = 200$, $penc = 0.1$, $r = 0.9$, $p = 1$, $\alpha = 220$.

absorbing state) can be derived as $D_d = \int_0^\infty G_D(t)dt$. From [12], we can get that $G_D(t) = e \cdot \exp(Tt) \cdot I$, consequently $D_d = e \cdot (-T^{-1}) \cdot I$, where e is a vector denoting the initial state probability vector e=$[1, 0, 0, \ldots, 0]$ and I is an all-one vector I=$[1, 1, \ldots, 1]$.

V. Model Validation

In order to evaluate the accuracy of our model, we apply it to mobility environment. As involved communication devices are basically the same in corresponding range and forwarding willingness in each trace, we simplify our model to a one-group situation (barely contains group A) to get the simulation results more precisely. In order to mitigate the effect brought about by the unequal capacity of the nodes that are randomly chosen, we assume a part of nodes rather than a single node in A is initially infected.

A. Methodology

We use Random WayPoint (RWP) model in the Opportunistic Networking Environment (ONE) simulator [19] with parameters set as follows: the number of users N is 200; simulation area is 500 $\times$ 500 m^2; nodes' mobility speed varies from 0.6 to 1.4 m/s; and link generating speed λ is 0.003. In this scenario, we get the link generating speed λ as the reciprocal of average inter-contact period while link perishing speed μ as the reciprocal of average contact period. Other parameters including bundle size α, percentage of nodes originally infected $penc$, ratio of nodes ought to be infected r and forwarding willingness p could be set optionally. With all the parameters above, we can use our model to get the theoretical result of average dissemination delay. On the other hand, the actual delay is obtained by replaying the propagation process: when two nodes' contact period is longer than α, the message is, with probability p, transmitted; and when at least rN nodes have been infected the process is ended. Now we quantify the distinction between theoretical results and actual delay upon a large variety of parameters.

B. Results

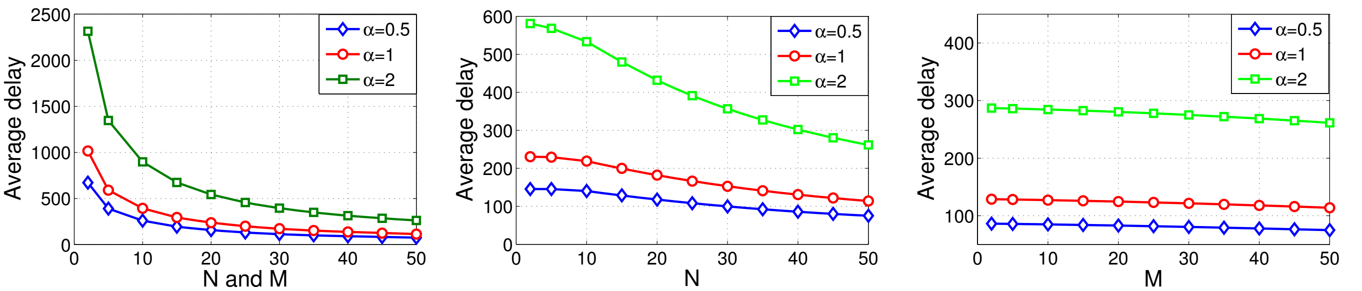
Fig. 2(a) compares the measured delay with the theoretical results of the model on various message sizes. We can see that, for $100 \leq \alpha \leq 260$, the measured delay and the theoretical results do match well and the Mean Squared Error (MSE) is about 0.037. When α is larger than 260, due to small-world effects, our model is over optimistic. However, as generally it is unlikely for such big messages to appear, our model still offers a precise estimation for average delay upon various message sizes. Fig. 2(b) shows that with increase of the percentage of nodes infected originally, both curves decreases almost linearly and MSE for these two curves is 0.079. As the ratio of nodes ought to possess the message comes near to 1 in Fig. 2(c), the average delay increases dramatically with a MSE of 0.1058 for measured delay and theoretical result. The almost horizontal curve when p is relatively large in Fig. 2(d) demonstrates that promoting forwarding willingness to 1 hardly worth its effort. The diversification between theoretical result and measured delay in this picture is also comparatively small with regard to a MSE of 0.1084.

These results show the accuracy of our model, and it does reflect properties of real-life message forwarding process. Thus exploiting our model to assess the influence of various parameters could offer valuable insight into the study in DTN real-life message propagation process.

VI. Performance Evaluation

In this section, we return to the two-group situation and quantify the performance of information dissemination delay derived from the proposed model to evaluate various parameters' influence. The parameters are set as follows, $\lambda_1 = 1/400$, $\lambda_2 = 1/1000$, $\mu_1 = 0.8$, $\mu_2 = 1$, r=0.8, N=50, M=50, $p_1 = 0.8$, $p_2 = 0.6$.

Figs. 4(a), (b) and (c) describe the relationship between average dissemination delay and the number of nodes for unequal message sizes. Fig. 4(a), in which the number of nodes in A and B increases simultaneously, shows that the average delay astonishingly degraded with the growth of N and M. Such a phenomenon might be attributed to the fact that each new node is a potential relay in the epidemic graph that might help in the spreading of message. Fig. 4(b) plots the average delay as a function of number of nodes in A while B's nodes remain static. It shows that, as N increases, the positive effect of A's new nodes alone working as relays could overweight, as ratio r remains static, the negative effect brought about by the growth in the number of nodes ought to be infected. Compared to Fig. 4(b), Fig. 4(c) illustrates that the increase of nodes in B



(a) Number of nodes in A and B (b) Number of nodes in A (c) Number of nodes in B

has a slighter effect over average delay, because B's nodes can hardly help to infect nodes in A as they are seldom connected concerning the rather small inter-group link generating speed.

Now we conclude from above upshots that the increase of number of nodes can remarkably decrease the average delay instead of increasing it when infecting ratio r is definite.

VII. Conclusion and Future Work

In this paper, we present a framework to evaluate the performance of information dissemination in delay tolerant networks. We apply this model to RWP model, and the results demonstrate it accurate to model the system. We also give theoretical results showing the influence of various parameters. We are now trying to apply more complex distributions to contact and inter-contact periods to obtain a more comprehensive model. Besides, utilizing our model to estimate the successful transmission rate within a limited period of time might also deserve a great deal of work in future.

Acknowledgment

This work is supported by National Nature Science Foundation of China (No. 61171065, No. 61021001) and Chinese National Major Scientific and Technological Specialized Project (No. 2010ZX03004-002-02), as well as the Program for Changjiang Scholars and Innovative Research Team in University (PCSIRT) and TNLIST.

References

[1] K. Lee, I. Rhee, J. Lee, S. Chong, and Y. Yi, "Mobile data offloading: how much can wifi deliver?" in *Proceedings of the 6th International COnference*. ACM, 2010, p. 26.

[2] X. Zhang, G. Neglia, J. Kurose, and D. Towsley, "Performance modeling of epidemic routing," *Computer Networks*, vol. 51, no. 10, pp. 2867–2891, 2007.

[3] F. Farnoud and S. Valaee, "Reliable broadcast of safety messages in vehicular ad hoc networks," in *INFOCOM 2009, IEEE*. Ieee, 2009, pp. 226–234.

[4] S. Burleigh, A. Hooke, L. Torgerson, K. Fall, V. Cerf, B. Durst, K. Scott, and H. Weiss, "Delay-tolerant networking: an approach to interplanetary internet," *Communications Magazine, IEEE*, vol. 41, no. 6, pp. 128–136, 2003.

[5] K. Fall, "A delay-tolerant network architecture for challenged internets," in *Proceedings of the 2003 conference on Applications, technologies, architectures, and protocols for computer communications*. ACM, 2003, pp. 27–34.

[6] R. Krishnan, P. Basu, J. Mikkelson, C. Small, R. Ramanathan, D. Brown, J. Burgess, A. Caro, M. Condell, N. Goffee *et al.*, "The spindle disruption-tolerant networking system," in *Military Communications Conference, 2007. MILCOM 2007. IEEE*. IEEE, 2007, pp. 1–7.

[7] P. Juang, H. Oki, Y. Wang, M. Martonosi, L. Peh, and D. Rubenstein, "Energy-efficient computing for wildlife tracking: design tradeoffs and early experiences with zebranet," in *ACM Sigplan Notices*, vol. 37, no. 10. ACM, 2002, pp. 96–107.

[8] J. Whitbeck, V. Conan, and M. de Amorim, "Performance of opportunistic epidemic routing on edge-markovian dynamic graphs," *Arxiv preprint arXiv:0909.2119*, 2009.

[9] A. Clementi, C. Macci, A. Monti, F. Pasquale, and R. Silvestri, "Flooding time in edge-markovian dynamic graphs," in *Proceedings of the twenty-seventh ACM symposium on Principles of distributed computing*. ACM, 2008, pp. 213–222.

[10] Y. Li, G. Su, D. Wu, D. Jin, L. Su, and L. Zeng, "The impact of node selfishness on multicasting in delay tolerant networks," *Vehicular Technology, IEEE Transactions on*, no. 99, pp. 1–1.

[11] M. Karaliopoulos, "Assessing the vulnerability of dtn data relaying schemes to node selfishness," *Communications Letters, IEEE*, vol. 13, no. 12, pp. 923–925, 2009.

[12] Y. Li, P. Hui, D. Jin, L. Su, and L. Zeng, "Evaluating the impact of social selfishness on the epidemic routing in delay tolerant networks," *Communications Letters, IEEE*, vol. 14, no. 11, pp. 1026–1028, 2010.

[13] A. Vahdat, D. Becker *et al.*, "Epidemic routing for partially connected ad hoc networks," Citeseer, Tech. Rep., 2000.

[14] T. Small and Z. Haas, "The shared wireless infostation model: a new ad hoc networking paradigm (or where there is a whale, there is a way)," in *Proceedings of the 4th ACM international symposium on Mobile ad hoc networking & computing*. ACM, 2003, pp. 233–244.

[15] R. Groenevelt, P. Nain, and G. Koole, "The message delay in mobile ad hoc networks," *Performance Evaluation*, vol. 62, no. 1-4, pp. 210–228, 2005.

[16] Z. Haas and T. Small, "A new networking model for biological applications of ad hoc sensor networks," *IEEE/ACM Transactions on Networking (TON)*, vol. 14, no. 1, pp. 27–40, 2006.

[17] A. Chaintreau, A. Mtibaa, L. Massoulie, and C. Diot, "The diameter of opportunistic mobile networks," in *Proceedings of the 2007 ACM CoNEXT conference*. ACM, 2007, p. 12.

[18] V. Lenders, J. Wagner, S. Heimlicher, M. May, and B. Plattner, "An empirical study of the impact of mobility on link failures in an 802.11 ad hoc network," *Wireless Communications, IEEE*, vol. 15, no. 6, pp. 16–21, 2008.

[19] A. Keranen, J. Ott, and T. Karkkainen, "The one simulator for dtn protocol evaluation," in *Proceedings of the 2nd International Conference on Simulation Tools and Techniques*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2009, p. 55.

[20] N. Eagle and A. Pentland, "Reality mining: sensing complex social systems," *Personal and Ubiquitous Computing*, vol. 10, no. 4, pp. 255–268, 2006.