

# Impact of Social Networks on Delay Tolerant Routing

Eyuphan Bulut, Zijian Wang and Boleslaw K. Szymanski

Department of Computer Science and Center for Pervasive Computing and Networking  
Rensselaer Polytechnic Institute, 110 8th Street, Troy, NY 12180, USA  
{bulute, wangz, szymansk}@cs.rpi.edu

**Abstract**—Delay Tolerant Networks (DTNs) are wireless networks in which at any given time instance, the probability of having a complete path from a source to destination is low due to the intermittent connectivity between nodes. Several routing schemes have been proposed for such networks to make the delivery of messages possible despite the intermittent connections. In this paper, in addition to intermittent connectivity which impacts routing most strongly, we also analyze the effects of underlying social structure over the communication network. In a social network, nodes interact in diverse ways so that some nodes meet each other more frequently than others. In the paper, we first propose a new network model to reflect the underlying social structure over the network nodes, then we study the effects of this model on the performance of multi-copy based routing algorithms. We also analyze the performance of routing and validate our analysis with simulations.

## I. INTRODUCTION

Delay Tolerant Networks (DTN) are wireless networks in which nodes are intermittently connected and there is no guarantee that a path exists from source to destination at any time instance. Today, there are many examples of such networks including wildlife tracking networks [1], military networks [2] and vehicular networks [3]. Moreover, the rapid and wide spread of different kinds of devices with wireless capabilities among people and their surroundings has enabled the possibility of opportunistic urban routing of messages in social networks. Such mode of communication, especially if combined with sensing (monitoring traffic etc.), attracted a great deal of interest because of enormous potential of collaborative data gathering via already deployed and human maintained devices, including cell phones and GPS devices.

Since the standard routing algorithms assume that the network is connected most of the time, they can not be applied to the routing of messages in a delay tolerant network. There are many routing algorithms proposed for such networks. Since the connectivity of the nodes is intermittent, these algorithms

make use of *store-carry-and-forward* paradigm in which messages are stored at nodes until an opportunity (meeting a new node) arise to forward the message. Although these proposed algorithms base their designs on different assumptions, the most appropriate assumption for real delay tolerant networks is zero knowledge about the network. In other words, since the future node contact times and their durations often can not be known exactly in a real DTN, the routing algorithms making their decisions based only on their local observations are the most useful ones.

Although many routing algorithms for DTNs were proposed in the literature, very few of them take into account the effect of social structure of the network on the design of the routing algorithm. It is always noted in many studies (i.e. [13]) that the movement of nodes in a mobile network and the interactions between nodes is not purely random and homogeneous but it is somewhat a mixture of homogeneous and heterogeneous behaviors. In other words, in a real mobile network, we always see grouping of nodes into communities such that the nodes within the same community behave similarly and the nodes from different communities show different behaviors.

Consider a Pocket Switched Network (PSN) which is a kind of social network in which people are intermittently connected via different wireless devices including cell phones and GPS devices. The connectivity between these human-carried devices is achieved when they get into the range of each other. In a social network, the relationship defining the frequency of connectivity between nodes can be various interdependencies including friendship, trade and status. That's why, for an efficient routing of messages in such networks, the mobility of nodes and the underlying community structure of the members of the whole society has to be carefully analyzed. For example, consider a high school network. Students in the same class have higher chance to see (so also to transfer data to) each other than the students from other classes (i.e. they can probably meet only during breaks).

In this paper, we study the effect of the social structure of the nodes in a delay tolerant network and show that considering this structure can help designing better routing algorithms. Since most of the routing algorithms for DTNs utilize the idea of distributing multiple copies of the same message, in this paper we study the effects of social structure of the network on multi-copy based routing algorithms. In the design of such algorithms for DTNs, there are two important

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issues to consider [10]: (i) the number of copies of each message that will be distributed to the network, and (ii) the selection of nodes to which the message is replicated. Both of these issues are studied by different authors in terms of the general routing idea in delay tolerant networks (i.e. [9]) but they are still open to research for social (community-based) networks such as PSNs which change the nature of standard delay tolerant networks due to the heterogeneous inter-meeting times of nodes in the network. In this paper, we study these issues from a community based network's point of view and demonstrate how they change in this setting.

The rest of the paper is organized as follows. In Section II we present related studies done on this topic. In Section III we describe our network model based on communities and then we discuss the challenges and tradeoff that affect the routing algorithm's performance in Section IV. Then in Section V, we provide our initial analysis for routing in such networks. In Section VI, we talk about our simulation model and its results which clearly show the effect of social structure on the performance of multi-copy based routing algorithms. We also validate there our analysis results using simulations. Finally, we offer conclusion and outline the future work in Section VII.

## II. RELATED WORK

Recently, several routing algorithms have been proposed for delay tolerant networks. However, some of them [14] have unrealistic assumptions (the existence of oracles which give information about future node meetings) which are not satisfied in real DTNs. Other than these algorithms, there are also some algorithms ([4]-[10]) which assume zero knowledge about the future network features (node meetings, contact durations etc.). In these algorithms, to increase the delivery rate of messages to the destination, two different approaches are applied. In the first one (i.e. [9]), multiple copies of the message are generated and distributed to the other nodes in the network and the delivery of at least one of these copies is expected in the future. Obviously, the more copies are used, the higher delivery ratio is achieved. But, on the other hand, with the increasing number of copies, network resources such as bandwidth and buffer space are wasted. In the second approach (i.e. [5]), a single copy of the message is transferred only to nodes having higher delivery likelihood. The histories of node meetings are utilized and possible future meetings of the nodes are predicted so that optimum paths to the destination are followed to increase the delivery ratio.

Although there are many algorithms utilizing the controlled flooding approach, only a few of them focus on message routing in social networks which also consist of intermittently connected nodes. What differentiate such networks from the general delay tolerant networks is their inner heterogeneous connectivity. In other words, there may be some set of nodes which meet more often than the others. Considering this partitioning of nodes into communities in social networks, there are some algorithms proposed to make the routing of messages more efficient in such networks. In [11], Daly et al. use both the betweenness and the similarity metric to increase

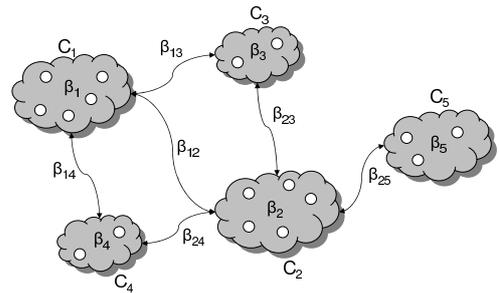


Fig. 1. A sample social network with five communities. Each community has different inner and inter-community meeting rates.

the performance of routing. In each contact of two nodes, the utility function containing these two metrics is calculated for each destination, then the node having higher utility value for a destination is given the messages. In [12], each node is assumed to have two rankings: global and local. While the former denotes the popularity (i.e. connectivity) of the node in the entire society, the latter denotes its popularity within its own community. Messages are forwarded to nodes having higher global rankings until a node in the destination's community is found. Then, the messages are forwarded to nodes having higher local ranking. Thus, the probability of finding the destination's community is increased. Then, after the message reaches the destination's community, the probability of meeting the destination is increased, so that the shortest delivery delay is attempted.

In this paper, we introduce an approach, different than the above studies, in which the problem of routing in social networks is seen from general perspective. We will not focus on the individual centrality values of nodes but utilize the average intermeeting times between group of nodes and discuss their effects on efficient routing.

## III. NETWORK MODEL AND ASSUMPTIONS

To illustrate the general picture of communities in a social network, we use the following model. Assume that there are  $m$  communities ( $C_1$  to  $C_m$ ) in the whole network and there are  $N_i$  nodes in community  $C_i$ . Moreover, assume that the nodes in community  $C_i$  get contact with the nodes in community  $C_j$  with an average intermeeting time of  $\beta_{ij}$  (for simplicity  $\beta_i = \beta_{ii}$ ). In other words, they have a chance to exchange their data in every  $t$  time units where  $t$  is a random variable exponentially distributed with mean  $\beta_{ij}$ . The nodes within the same community are considered identical in terms of meeting behavior with other nodes, but the nodes from different communities are considered having different behaviors. Accordingly, both the homogeneity and the heterogeneity are embedded into the network structure. A sample network with five communities is shown in Figure 1.

The beauty of this model is that it successfully monitors the general behavior of nodes in community-based social networks. It avoids dealing with individual behaviors of nodes and provides only the average intermeeting time of nodes both inside and outside the community. Consider the examples of

real life PSN scenarios. Nodes get in contact with each other depending on their relations in the society. Moreover, this contact times may sometimes happen unpredictably. However, even in such cases, we claim that on the average there are stable intra- and inter-community intermeeting times in the whole network and these can be found using the histories of node meetings.

#### IV. CHALLENGES AND TRADEOFF OF EFFICIENT ROUTING

In multi-copy based routing algorithms, the main goal is to deliver a message from a source node  $s$  to a destination node  $d$  by generating multiple copies of the message and spreading them to different nodes in the network. Once one of the copies is delivered, the message itself is delivered. Clearly, the number of copies generated and distributed to the network defines the characteristics (i.e. delay, cost) of the delivery. This is also the main reason of why researchers always have focused on the design of routing algorithms with efficient number of copies of the message.

It is obvious that we can increase the delivery probability and decrease delivery delay of a message by just increasing the number of copies that will be distributed to the network. However, we also need to distribute the copies by taking into account the meeting frequencies between nodes (effect of community structure). Assume that  $s$  has a message to deliver to  $d$  in the network. Furthermore, assume that  $s$  is allowed to distribute at most  $L - 1$  copies of the message to the other nodes (the other nodes are not allowed to replicate the message). Therefore, once all copies of the message are given to other nodes, the total number of copies in the network will be  $L$ . The instant strategy that comes to mind is to allow  $s$  to give these copies to the first  $L - 1$  nodes that it meets in the network. In this way, the fastest distribution of the copies is achieved, the waiting phase starts immediately thereafter, and the delivery of the message is attempted independently by each of the nodes having the message copy. If  $s$  and  $d$  are in the same community, this strategy is reasonable and works well especially in scenarios where the future node meetings are unknown.

However, if  $s$  and the destination are not in the same community, this strategy loses its effectiveness due to its copy distribution without considering the community information. The copies may be given to nodes which have low chance to meet  $d$ , thus to deliver the message. For example, consider a society with three communities (source's community ( $C_s$ ), destination's community ( $C_d$ ) and another community ( $C_e$ )). Moreover, assume that the intermeeting times between the nodes of each community and different communities hold the following reasonable relations:  $\beta_s = \beta_d = \beta_e$ ,  $\beta_{sd} = \beta_{se} = \beta_{de}$  and  $\beta_s \ll \beta_{sd}$ . In this sample scenario, there are three cases of message copying in terms of its effects on the copying and delivery time:

- $s$  can give copies to nodes within its own community. Since it meets these nodes more frequently than others, the duration of message copy distribution to these nodes takes less time than copying to  $C_d$ 's nodes. On the other

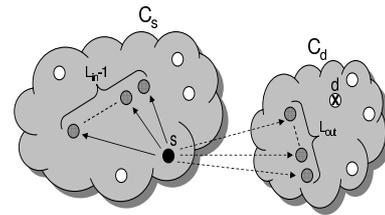


Fig. 2. Distribution of copies to source's and destination's communities.

hand, since the nodes in  $C_s$  meet the nodes (i.e.  $d$ ) in  $C_d$  less frequently than  $C_s$ 's nodes, the probability of message delivery is lower, so that average delivery delay gets longer.

- $s$  can give copies to nodes that are in  $C_d$ . This provides less waiting for nodes to meet  $d$  after they have copies. However,  $s$  meets with these nodes less frequently than the nodes in  $C_s$  so that the copying phase is longer.
- $s$  can give copies to nodes that are in  $C_e$ . Since  $s$  meets these nodes infrequently and after the copying process is done, these nodes meet the destination infrequently, giving copies to such nodes is not an efficient strategy to reduce the delivery delay.

Looking at the above three cases, it is clear that the first and second cases have tradeoffs in terms of copying and waiting durations. But the third case has disadvantages during both the copying and waiting times. Therefore, an efficient strategy to decrease the delivery delay must take into account the first two cases in the distribution of message copies, but the number of copies used in either case must be carefully decided to obtain the optimum delivery delay. In the next section, we provide an analysis of delivery delay with different number of copies given to source's community ( $L_{in}$ ) and destination's community ( $L_{out}$ ).

#### V. ANALYSIS

In this section, we will compute the expected delivery delay that can be achieved in the network where the source node  $s$  gives the copies of the message either to the nodes in  $C_s$  or  $C_d$ . For the sake of simplicity, we make the following assumptions. Let  $N = n + 1$  denote the number of nodes in  $C_s$  and  $C_d$  ( $N_s = N_d = N$ ). We know that, on the average,  $s$  meets all other  $n$  nodes in its own community within  $\beta_s$  time units. Therefore, if we assume that the average time of meeting any other node is a single time unit, then it follows that  $\beta_s = n$ . Moreover we assume that  $\beta_{sd} = k\beta_s = k\beta_d$  where  $k > 1$ .

In this model, as it is seen in Figure 2, there are two independently running processes by which delivery can happen:

**Local Spraying:** Source distributes  $L_{in} - 1$  additional copies of the message (altogether  $L_{in}$  copies with copy in  $s$ ) to the other nodes that are in the same community with itself ( $C_s$ ). Then, each of these nodes can deliver the message to the destination with probability  $\frac{1}{nk}$  in each time unit. Since from

time  $i - 1$  to  $i$ , on the average, there are  $i^1$  nodes having the message copy in  $C_s$ , the total gained probability of delivery by the nodes in  $C_s$  becomes  $\frac{i}{nk}$  at time  $i$ . The case of direct delivery of the message to the destination by the source is also included in this type of delivery, which occurs of course with the same probability.

**Global Spraying:** Source gives  $L_{out} = L - L_{in}$  copies of the message to the nodes that are in the same community with destination ( $C_d$ ). Then, each of these nodes can deliver the message to the destination with probability  $\frac{1}{n}$  in each time unit. The number of nodes having copy in  $C_d$  is zero at the beginning and on the average source can give a copy to a node in  $C_d$  in every  $k^{th}$  unit. As a result, we can assume that in a time unit, there is only  $1/k$  copies given to such nodes so that the total probability of delivery by the nodes (in  $C_d$ ) having copy becomes  $\frac{i-1}{nk}$  (i.e. until time 1 it is zero).

Now, we will calculate both the probability of delivery and the expected delivery time of a message in such a network model. We need to combine the probabilities of two processes in a time unit. Clearly, there are three different phases in the delivery process of the message. In the first (*All Spraying*), both the local and global spraying will continue and at each time unit the delivery probability will be increased by both processes. In the second phase (*Mixed*), only one of these processes will continue spraying, the other one will stop spraying and enter waiting phase. Depending on the parameters  $L_{in}$  and  $k$ , either of these processes can end up spraying before the other one. We need to consider this in our calculation. Finally, in the third phase (*All Waiting*), both of these processes stop spraying and run their waiting processes which means that they contribute to the delivery probability with constant copy counts.

Local spraying ends before global spraying if the following condition is satisfied:

$$L_{in} - 1 \leq k(L - L_{in}), \text{ so when}$$

$$L_{in} \leq \frac{k}{k+1}L + \frac{1}{k+1}$$

According to these observations, if local spraying ends before global spraying (case A), then the delivery probability of a message in *All Spraying* phase can be calculated as:

$$P_1 = \sum_{i=1}^{L_{in}-1} D'_1(i) \left( \frac{2i-1}{nk} \right), \text{ where}$$

$$D'_1(i) = \prod_{j=1}^{i-1} \left( 1 - \frac{2j-1}{nk} \right)$$

Here,  $\frac{2i-1}{nk}$  denotes the probability of delivering at the  $i^{th}$  time unit and the product term denotes the probability of not delivering before the  $i^{th}$  time unit.

In the second phase (*Mixed* phase), since the local process finishes its spraying, the probability of delivery at a time unit

<sup>1</sup>For simplicity, we ignore the cases where  $s$  meets the nodes already having copy. Since we mostly study the scenarios in which  $L_{in} \ll N_s$ , the effect of these cases on the total probability is very low.

changes and the total delivery probability becomes:

$$P_2 = \sum_{i=L_{in}}^{k(L-L_{in})} C_1 D'_2(i) \left( \frac{L_{in} + (i-1)}{nk} \right), \text{ where}$$

$$D'_2(i) = \prod_{s=L_{in}}^{i-1} \left( 1 - \frac{L_{in} + (s-1)}{nk} \right)$$

$$C_1 = \prod_{j=1}^{L_{in}-1} \left( 1 - \frac{2j-1}{nk} \right)$$

In the *All Waiting* phase, since spraying of copies ends in both processes, then the delivery probability is increased by a constant probability at each time unit. Hence, the total delivery probability in the third phase is computed as:

$$P_3 = \sum_{i=k(L-L_{in})+1}^{\infty} C_1 C_2 D'_3(i) \left( \frac{L_{in} + k(L-L_{in})}{nk} \right)$$

$$D'_3(i) = \left( 1 - \frac{L_{in} + k(L-L_{in})}{nk} \right)^{i-k(L-L_{in})-1}$$

$$C_2 = \prod_{s=L_{in}}^{k(L-L_{in})} \left( 1 - \frac{L_{in} + (s-1)}{nk} \right)$$

But if the global spraying ends before local spraying (Case B) then the formulations need to be updated due to changes in the boundaries between the three phases:

$$P_1 = \sum_{i=1}^{k(L-L_{in})} D'_1(i) \left( \frac{2i-1}{nk} \right)$$

$$P_2 = \sum_{i=k(L-L_{in})+1}^{L_{in}} C_1 D'_2(i) \left( \frac{k(L-L_{in})+i}{nk} \right)$$

$$P_3 = \sum_{i=L_{in}}^{\infty} C_1 C_2 D'_3(i) \left( \frac{L_{in} + k(L-L_{in})}{nk} \right)$$

where,  $D'_1(i)$  remains same as in above but  $D'_2(i)$ ,  $D'_3(i)$ ,  $C_1$  and  $C_2$  change as follows:

$$D'_2(i) = \prod_{s=k(L-L_{in})+1}^{i-1} \left( 1 - \frac{k(L-L_{in})+s}{nk} \right)$$

$$D'_3(i) = \left( 1 - \frac{L_{in} + k(L-L_{in})}{nk} \right)^{i-L_{in}}$$

$$C_1 = \prod_{j=1}^{k(L-L_{in})} \left( 1 - \frac{2j-1}{nk} \right)$$

$$C_2 = \prod_{s=k(L-L_{in})+1}^{L_{in}} \left( 1 - \frac{k(L-L_{in})+s}{nk} \right)$$

Using the above formulations, we can compute the average delivery probability in each of the three phases separately. As an example, we calculated these probabilities for two different configurations and plotted the results in Figures 3 and 4. While in the former graph ( $L, k$ ) pair is assumed to be (10, 5), in

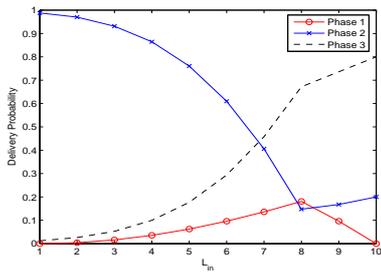


Fig. 3. Delivery probabilities when  $k = 5$  and  $L = 10$

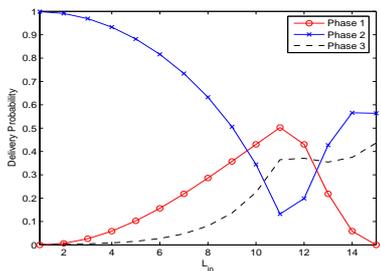


Fig. 4. Delivery probabilities when  $k = 3$  and  $L = 15$

the latter they are assigned (15, 3) values ( $N=50$ ). In both of these figures the delivery probability in the first period reaches the maximum at the biggest integer value of  $L_{in}$  that is less than the boundary value. That point is also the optimum point for the second period because the minimum probability is achieved at this point. This is because the duration of second period gets smaller when  $L_{in}$  gets closer to boundary point. It is also important to note that when  $L_{in} = 1$ , the message is most probably ( $\approx 100\%$ ) delivered in the second phase (only global spraying) but on the other hand, when  $L_{in} = L$ , the delivery probability in this mixed phase (only local spraying) is much smaller than 100%. This is caused by the longer duration of global spraying than local spraying (when  $L_{in} = 1$  and  $L_{out} = L - 1$ ) which also increases the delivery probability of the message (in *Mixed* period) by nodes already having copy (in  $C_d$ ) while source is still trying to distribute remaining copies to the nodes in  $C_d$  (which of course takes longer).

The above formulations are to estimate the delivery probability in each of the three phases. To estimate the expected delivery time in a period  $i$ ,  $ED_i$ , we simply multiply  $P_i$  by  $i$ . Then, summing these  $ED_i$  values gives us the expected delivery time in such a spraying algorithm. We will show the computed  $ED$  values for the same  $(L, k)$  pairs used in the previous figures and validate the results with simulations in the next section.

## VI. SIMULATION RESULTS

We developed a Java-based DTN simulator to see the effects of different  $L_{in}$  and  $L_{out}$  values. For our initial simulations, we work on a network where the messages are distributed either the source's community or destination's community (we

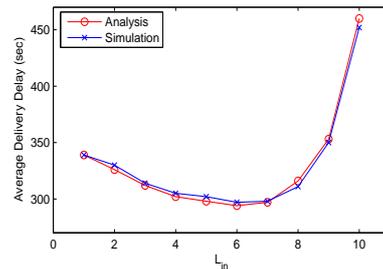


Fig. 5. Simulation vs. analysis showing the expected delivery delay when  $k = 5$  and  $L = 10$

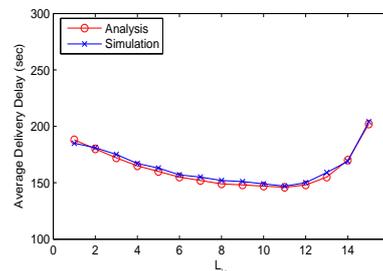


Fig. 6. Simulation vs. analysis showing the expected delivery delay when  $k = 3$  and  $L = 15$

will work on more complex social network models in the future work). That's why we created a network with two communities in each of which there are 50 mobile nodes. We deploy the nodes onto a torus of the size 300 m by 300 m. All nodes are assumed to be identical and their transmission range is set at  $R = 10$  m. Nodes move according to random direction mobility model [13]. The speed of a node is randomly selected from the range [4, 13]m/s and its direction is also randomly chosen. Then, each node goes in the selected random direction at the assigned speed for an epoch duration. Each epoch's duration is again randomly selected from the range [8, 15]s. The meeting times of nodes are assumed to be independent and identically distributed (IID). Furthermore, we also assume that the buffer space in a node is infinite, the communication between different pair of nodes is perfectly separable and free space propagation model is used. We used different values of  $k$  to see its effect on the performance of the algorithm. To simulate nodes from different communities ( $C_s$  and  $C_d$ ) which meet each other in every  $\beta_{sd} = k\beta_s$  time units on the average, we ignored the first  $k - 1$  meetings of such node pairs and treated the  $k^{th}$  meeting as a real meeting (as a reminder, the average meeting time between two encounters of any pair of nodes is  $\beta_s$  or  $\beta_d$ ).

Assuming that the TTL of messages is much longer than the expected delivery delay (justifiable in DTNs), we have created messages at a randomly selected source node for delivery to a randomly selected destination node in the other community. Then, we collected some useful statistics from the network. The results are averaged over 3000 runs.

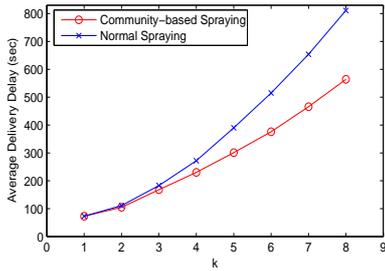


Fig. 7. Average delivery delay with different  $k$  values when  $L = 10$

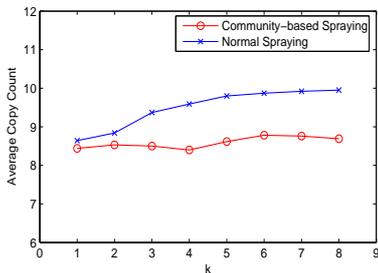


Fig. 8. Average copy count used per message with different  $k$  values when  $L = 10$

First of all, to validate the analysis computation of average message delivery delay, we did simulations with two different  $(L, k)$  pairs. Figures 5 and 6 show the comparison of analysis and simulation results in terms of average delivery delay when  $(10, 5)$  and  $(15, 3)$  pairs are used, respectively. Since a single time unit is defined differently in our analysis, we adjusted results of the analysis accordingly. From these two graphs, we observe that the analysis and simulation results are matching, proving the correctness of the analysis.

We have also compared two spraying strategies: 1) Community based spraying where the  $L_{in}$  and  $L_{out}$  (in total  $L$ ) values are set such that the minimum delay is achieved<sup>2</sup> 2) Traditional spraying algorithm [7] in which copies are given to the first  $L - 1$  nodes met by the source node. Figures 7 and 8 show the average message delivery delay and the average message copy count (and therefore the cost) achieved in both algorithms with different  $k$  values when  $L = 10$ . It is clear that as  $k$  increases, the difference of delivery delay obtained by both algorithms gets bigger. Furthermore, community based spraying algorithm also outperforms normal spraying algorithm in terms of count of copies used per message (when  $k = 8$ , the improvement is around 15%). Since in the former, the distribution of copies to other nodes is designed considering the community structure of the network nodes, we get improvements in both of these metrics.

<sup>2</sup>Note that the optimal  $L_{in}$  value is very close to but not exactly  $k \frac{L}{k+1}$ . To find the exact optimum value is the subject of our future work.

## VII. CONCLUSION AND FUTURE WORK

In this paper, we focus on the routing problem in delay tolerant networks in which nodes are disconnected most of the time and yet display a group behavior. We first propose a new social network model representing an abstraction of node meetings in community-based networks. Then, we discuss the effects of distributing different number of copies to different communities on the performance of routing. We analytically calculate the expected delivery delay in a sample network scenario and validate the results with simulations. Furthermore, we compare the minimum delay achieved when optimal  $L_{in}$  is used with the delay of traditional spraying algorithm in which message copies are distributed without considering the underlying community structure in the network. We observed that considering the community structure and distributing copies accordingly outperforms the normal spraying both in terms of average delivery delay and the average copy count used per message.

As a future work, we will analyze the optimum distribution of copies to different communities. To this end, we would like to extend our fundamental analysis shown here to be applicable to many communities with various interaction rates between them. It should be noted that, the message copies must be distributed carefully in this case because different interaction rates between communities can make the delivery of messages over multiple communities (i.e.  $C_s$  to  $C_e$  to  $C_d$ ) more efficient than directly sending them from  $C_s$  to  $C_d$ .

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