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Epidemic Routing Performance in DTN With Selfish Nodes

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ABSTRACT Message transmission in a delay-tolerant network (DTN) closely depends on the cooperation between nodes. However, nodes in real-world may be selfish so they may not be fully cooperative, and the behavior may have a certain impact on the message transmission process. Based on the famous ordinary differential equation (ODE), this paper presents the corresponding mathematical model to analyze the influence of selfish behaviors on two famous hop-limited flooding policies (*lazy L-hop limited flooding* and *L-hop limited flooding*). Then, it runs some simulations based on both synthetic and real trace and proves the exactitude of the model. The theoretical results demonstrate that the selfish behaviors significantly decrease the performance. However, if the message has a bigger lifetime, these algorithms are more robust to the selfish behaviors. In addition, the theoretical results also show that the influence depends on the network structure (the communities' number in the network). On the other hand, the location of the source also has a certain impact on the performance.

INDEX TERMS Delay tolerant networks, hop- limited flooding, selfish behaviors, performance evaluation.

I. INTRODUCTION

Ubiquitous sensor network (USN) tries to connect all possible sensors in a specific area. Those sensors may be distributed and move randomly, which make the USN dynamic frequently. In particular, the communication link in USN may be disrupted, and can be modeled as Delay Tolerant Networks (DTN) [1]. In fact, DTN has been used in many scenarios, such as the deep-space exploration networks [2], social networks [3], and vehicular networks [4], etc. Due to the disruption of links, message dissemination protocols in traditional ad hoc networks, which relay on the end-to-end paths, may not work in DTN efficiently.

In order to overcome the network partitions, nodes in DTN communicate with each other based on the SCF (*store*, *carry*, *forward*) mode [5], which needs the nodes to work in a cooperative way. However, in the real world, most nodes exhibit selfish behaviors [6], [7] and are not willing to forward the message as relay nodes. The selfish behaviors can be divided into two categories, individual selfishness and social selfishness, respectively. On one hand, people may not be willing to forward messages to others when they get message, as the process consumes energy. This phenomenon shows that nodes may be selfish in the process of message dissemination, and this behavior can be seen as *individual selfishness* [8]. On the other hand, people have different social ties with different people and the communities can be formed [9], [10]. Based on such phenomenon, people show the *social selfishness* [11], which means that a specific person A has more incentives to help another people B, if they belong to the same community.

In this paper, we mainly explore the impact of selfish behaviors on the process of message dissemination. In particular, message is propagated through a flooding way, that is, each contact between nodes can be exploited to transmit the message. More precisely, we adopt a hop-limited flooding mechanism [12]. One famous example of such policies is 2-hop method [13]. We explore the impact of selfish behaviors on the performance of two more general hop-limited flooding policies, which can be seen as *lazy L-hop limited flooding* and *L-hop limited flooding* [12].

There are fewer works that evaluate the performance of flooding algorithms theoretically when the maximal hop is limited. The work in [12] characterized the performance of such algorithms in terms of completion time (the time it takes for a given proportion of nodes to receive message), but it ignores the selfish behaviors.

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Most of works about the analysis of selfishness ignore the *social selfishness*, such as [6]–[8]. To overcome this problem, the work [14] proposes a model to analyze the influence of *social selfishness* on the epidemic routing, and then it is extended to the case under multicasting [15]. However, both works assume that the message is transmitted in the flooding mode, that is, the maximal value of the hop is not limited. Further, they assume that there are only two communities. In fact, when the network has multi-communities, the state space of the method in work [14], [15] is too big and it is hard to calculate. To overcome these problems, we get some contributions in this paper, which can be summarized as follows:

- Based on the famous ODE (ordinary differential equation), we present a mathematical framework to model the message transmission process of two specific hop limited flooding policies, which are *lazy L-hop limited flooding* and *L-hop limited flooding* algorithms. In particular, this model considers two kinds of selfish behaviors and they are individual selfishness and social selfishness, respectively.
- Extensive simulations based on both synthetic and real trace demonstrate the accuracy of the model and the average deviation is not bigger than 4.76%. Extensive theoretical results show many interesting characteristics of the model. For example, the influence of both selfish behaviors is small when the message lifetime is big. In addition, the performance may decrease with the number of communities.

The rest of this paper is organized as follows. The related works are briefly introduced in Section II. Section III gives the message propagation model for two special hop-limited flooding, respectively. Simulation and numerical results are shown in Section IV. Finally, we summarize our work in Section V.

II. RELATED WORKS

The basic routing method in DTN is epidemic routing (ER) [16]. It works in the flooding way and it will consume too much energy. Recently, lots of methods have been presented to overcome the problem, such as the probabilistic forwarding policy [17], [18], hop-based forwarding policy [12], etc. These policies have both strengths and limitations, so how to evaluate their performance is very important. The work in [19] studied the performance of epidemic routing method based on the sparsely exponential graph and then the problem was explored again with heterogeneous nodes in [20]. The authors in [21] explored the delay of ER with network-coding policy. The work [22] studied the information propagation speed in bidirectional vehicular delay tolerant network. The work [23] studied the performance of ER policy when the nodes have dynamic social behaviors. The authors in [24] studied the routing performance with contention. Similar to our work, [25] explored the performance of hop limited flooding policy, but it fails to consider the *lazy L-hop limited flooding* policy, so it is different from our work.

On the other hand, above works ignore the influence of selfishness. A simulation method is proved in [26] to analyze the influence of selfishness. Then, many theoretical methods are presented, such as [27]–[30]. In particular, the work [29] is very similar to our work. However, different from our work, [29] just considers the count limited routing policy, where each node can forward a message to at most L nodes.

III. THEORETICAL FRAMEWORK

In this paper, we address the message transmission problem in DTN and analyze the impact of two kinds of selfish behaviors on the performance of two hop-limited epidemic routing algorithms. There is a source S and only S is carrying message. The message is forwarded in the network as time goes by. Besides the source, other nodes can be seen as the relay nodes. The number of the relay nodes is assumed to be N, which forms K communities. Then, let N_i denote the number of the relay nodes in i-th community, and (1) follows.

$$\sum_{i=1}^{K} N_i = N \tag{1}$$

In addition, the source may be in any community. If it is in i-th community, the total number of nodes in i-th community is $N_i + 1$.

Nodes in the network communicate with each other only when they come into the transmission range of each other, which means a communication contact, so the mobility rule of nodes is critical. In this paper, we assume that the occurrence of contacts between two nodes follows a Poisson distribution. This assumption has been used in wireless communications for many years, and many works show its rationality [31]–[35]. Therefore, we can assume that the inter-contact time conforms to an exponential distribution with parameter λ.

Later, we will present the definitions of two hop-limited flooding polices. Before the introduction, we first define the state of nodes. Specially, we let -1 denote the state of nodes without message, and suppose that the source's state is 0. As shown in [12], nodes can receive message only from nodes which have smaller state. However, nodes that are not carrying message (in state -1) are special, and they can obtain message from nodes that can forward message to others (whose state is bigger than -1). Obviously, the state of the source is in state 0 all the time. If a node k receives message from node c and the node c is in state j, node k will change its state to $j+1$. It is easy to see that the state corresponds to the number of hops of the path through which the message was received.

Lazy L-Hop Limited Flooding [12]: Suppose the hop count is L. When node m and n meet, if node m has the message and is in state $j < L$, but n does not have message, then the message will be transmitted to$n$. In addition, node n will change its state to $j+1$.

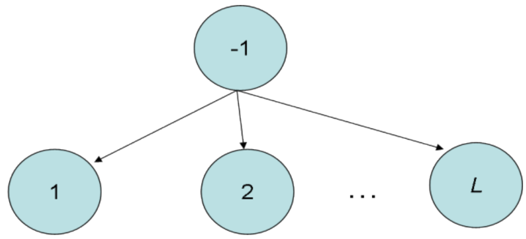

FIGURE 1. State transfer process of *lazy L-hop limited flooding*.

L-Hop Limited Flooding [29]: Suppose the hop count is L. If only one node has the message, the transmission process is the same as the *Lazy L-hop limited flooding* policy. However, if both nodes m and n have message, which are in state i and j, respectively, then if $i < j$, the state of node n will update to $i+1$.

To denote the selfishness, we assume that nodes in community i help the nodes in community j with probability p_{ij}. If $i = j$, they are the same community, so p_{ij} can be seen as the *individual selfishness*. Otherwise, it is the *social selfishness*. In the *L-hop limited flooding algorithm*, nodes may update their state if they encounter with one node that has smaller state and has message. However, due to the impact of selfishness, nodes may not tell its state to others. In other words, the selfish nature can have certain impact on the updating process, too. For simplicity, we assume that level of selfishness is the same as that in the forwarding process. For example, node m (in i-th community) encounters with node n (in j-th community), m tells its state to n with probability p_{ij}. Other cases with different level of selfishness will be our future work.

Then, we use $X_j^i(t)$ to denote the i-th community's nodes that remains in state j at time t. We begin to explore the theoretical model for above two flooding polices in the next subsection, respectively.

A. THEORETICAL MODEL OF LAZY L-HOP LIMITED FLOODING

According to the definition of *Lazy L-hop limited flooding algorithm*, the state transfer process of the nodes can be obtained easily, which is shown in Fig.1. From Fig.1, we can see that only nodes in state -1 can change their state. This is because only nodes that do not have message can obtain message.

Given a small time interval Δt, we can obtain (2) similar to [25],

$$X_j^i(t+\Delta t) = X_j^i(t) + \sum\nolimits_{k\in\{X_{-1}^i(t)\}} \varphi_{-1\to j}^k(t, t+\Delta t), \quad j \in [1, L] \tag{2}$$

All of the nodes remain in state -1 and belong to community i at time t forms a set, which is denoted as $\{X_{-1}^i(t)\}$. Then, we define an event $\varphi_{-1\to j}^k(t, t+\Delta t)$, if the node k changes its state from -1 to j from time t to $t+\Delta t$, we have $\varphi_{-1\to j}^k(t, t+\Delta t) = 1$. Otherwise, it equals to 0. Then, according to [29], (3) follows.

$$\begin{aligned} &p(\varphi_{-1\to j}^k(t, t+\Delta t) = 1) \\ &= 1 - \prod\nolimits_{m=1}^{K} \\ &\quad \times p(k \textit{ does not receive message from node } f)^{X_{j-1}^m(t)} \\ &= 1 - \prod\nolimits_{m=1}^{K} (1 - p_{mi}(1 - \exp(-\lambda\Delta t)))^{X_{j-1}^m(t)}, \quad j \in [1, L] \end{aligned} \tag{3}$$

The number of elements in set $\{X_{-1}^i(t)\}$ is $X_{-1}^i(t)$, and every one of them is independent. Therefore, through combining with (2) and (3), (4) follows.

$$E(\dot{X}_j^i(t)) = \lim_{\Delta t\to 0} \frac{E(X_{-1}^i(t))E(1 - \prod_{m=1}^{K} (1 - p_{mi}(1 - \exp(-\lambda\Delta t)))^{X_{j-1}^m(t)})}{\Delta t} \tag{4}$$

From (4), we can easily get the following equation,

$$E(\dot{X}_j^i(t)) = \lambda E(X_{-1}^i(t)) \sum\nolimits_{m=1}^{K} p_{mi} E(X_{j-1}^m(t)), \quad 1 \le i \le K, \quad 1 \le j \le L \tag{5}$$

As shown above, only the source S is in state 0, and its state never changes. In this case, we can obtain,

$$E(\dot{X}_j^i(t)) = 0, \quad 1 \le i \le K, \; j = 0 \tag{6}$$

Similar to (2), we can further obtain,

$$X_j^i(t+\Delta t) = X_j^i(t) - \sum\nolimits_{k\in X_{-1}^i(t)} \tau_{-1\to}^k(t, t+\Delta t), \quad j = -1 \tag{7}$$

The event $\tau_{-1\to}^k(t, t+\Delta t)$ shows whether the node k gets message. If this node successfully gets the message, it is 1, otherwise it equals to 0. Then, we have,

$$\begin{aligned} &p(\tau_{-1\to}^k(t, t+\Delta t) = 1) \\ &\quad = 1 - \prod\nolimits_{m=1}^{K} (1 - p_{mi}(1 - \exp(-\lambda\Delta t)))^{\sum_{l=0}^{L-1} X_l^m(t)} \end{aligned} \tag{8}$$

Similar to (5), then (9) follows.

$$E(\dot{X}_j^i(t)) = -\lambda E(X_{-1}^i(t)) \sum\nolimits_{m=1}^{K} p_{mi} \sum\nolimits_{l=0}^{L-1} X_l^m(t), \quad j = -1, \quad i \in [1, K] \tag{9}$$

B. THEORETICAL MODEL OF L-HOP LIMITED FLOODING

For the *L-hop limited flooding*, nodes that carry message may change their state, too. In particular, if node m with state i (>-1) encounters with node n with state $j (i < j)$, and node m tells its current state to n, the node n will update its state to $i+1$. Therefore, we can get the state transfer process shown in Fig.2. From Fig.2(b), we can see that nodes in state j $(1 < j < L)$ can change to state i. On the other hand, nodes whose state is greater than j may change its state to j. In addition, nodes that do not have message (in state -1) may change to state j, too. If $j = -1$, it may change to any state whose value

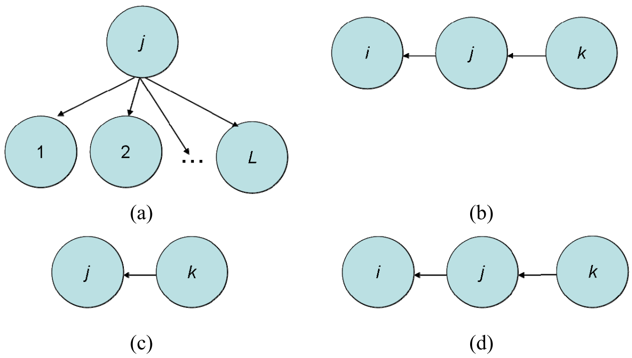

FIGURE 2. **The transfer process of state j with *L-hop limited flooding*. (a) $j = -1$. (b) $1 < j < L, 0 < i < j, j < k \le L$ or $k = -1$. (c) $j = 1, j < k \le L$ or $k = -1$. (d) $j = L, 0 < i < j, k = -1$.**

is bigger than 0 (see Fig.2 (a)). From Fig.2(c), we can see that if $j = 1$, only nodes that do not have message or whose state is bigger than 1 can change to j. If $j = L$, a node in state j may update the current state if it encounters a node with lower state and carrying message. If the node j obtains message from a node which is in state $L - 1$, its state will change to j $(= L)$. Note that if $j = 0$, nodes in state j cannot change its state anymore and nodes cannot change to state 0 from other states. Therefore, state 0 can be seen as the absorption state, which is similar to the case in the *Lazy L-hop limited flooding*.

From above analysis, we have the following equation,

$$\begin{aligned} X_j^i(t+\Delta t) &= X_j^i(t) + \sum\nolimits_{k\in\{X_{-1}^i(t)\}} \varphi_{-1\to j}^k(t, t+\Delta t) \\ &\quad - \sum\nolimits_{k\in\{X_j^i(t)\}} \sigma_{j\downarrow}^k(t, t+\Delta t) \\ &\quad + \sum\nolimits_{k\in\{X_{>j}^i(t)\}} \rho_{\to j}^k(t, t+\Delta t), \quad 1 < j < L \end{aligned} \tag{10}$$

The event $\sigma_{j\downarrow}^k(t, t+\Delta t)$ denotes whether the node k in state j changes its state in time interval $[t, t+\Delta t]$. If the node changes its state, the event is 1, otherwise it is 0. The event $\rho_{\to j}^k(t, t+\Delta t)$ denotes whether the node k changes to state j from bigger state in interval $[t, t+\Delta t]$. Similarly, if the event happens, it equals to 1. Then, we define $X_{>j}^i(t)$ as the set of nodes in community i and their state is greater than j. Furthermore, $|X_{>j}^i(t)|$ is the cardinality of $X_{>j}^i(t)$, so we have,

$$\left|X_{>j}^i(t)\right| = \sum\nolimits_{l=j+1}^{L} X_l^i(t), \quad j < L \tag{11}$$

Obviously, the node k changes its state from j to another one only when it meets a node whose state satisfies $-1 < h <$ j-2. Therefore, we will get,

$$\begin{aligned} &P(\sigma_{j\downarrow}^k(t, t+\Delta t) = 1) \\ &\quad = 1 - \prod\nolimits_{m=1}^{K} (1 - p_{mi}(1 - \exp(-\lambda\Delta t)))^{\sum_{l=0}^{j-2} X_l^m(t)}, \\ &\quad 1 < j \le L \end{aligned} \tag{12}$$

Similarly, if the node k changes its state from bigger state to j, it should get the message from a node which is in state j-1. Then, (13) follows.

$$\begin{aligned} &p(\rho_{\to j}^k(t, t+\Delta t) = 1) \\ &\quad = 1 - \prod\nolimits_{m=1}^{K} (1 - p_{mi}(1 - \exp(-\lambda\Delta t)))^{X_{j-1}^m(t)}, \\ &\quad 1 \le j < L \end{aligned} \tag{13}$$

Combining (3), (10), (12) and (13), we can obtain the expectation as follows,

$$\begin{aligned} &E(X_j^i(t+\Delta t)) \\ &= E(X_j^i(t)) + E(X_{-1}^i(t))E(\varphi_{-1\to j}^k(t, t+\Delta t)) \\ &\quad - E(X_j^i(t))E(\sigma_{j\downarrow}^k(t, t+\Delta t)) \\ &\quad + E(\sum\nolimits_{l=j+1}^{L} X_l^i(t))E(\rho_{\to j}^k(t, t+\Delta t)), \quad j \in [2, L-1] \\ &\quad \Rightarrow \frac{E(X_j^i(t+\Delta t)) - E(X_j^i(t))}{\Delta t} \\ &= \underbrace{\frac{E(X_{-1}^i(t))E(\varphi_{-1\to j}^k(t, t+\Delta t))}{\Delta t}}_{EX1} \\ &\quad - \underbrace{\frac{E(X_j^i(t))E(\sigma_{j\downarrow}^k(t, t+\Delta t))}{\Delta t}}_{EX2} \\ &\quad + \underbrace{\frac{E(\sum_{l=j+1}^{L} X_l^i(t))E(\rho_{\to j}^k(t, t+\Delta t))}{\Delta t}}_{EX3} \end{aligned} \tag{14}$$

As shown in section III-A, we have,

$$\lim_{\Delta t\to 0} EX1 = \lambda E(X_{-1}^i(t)) \sum\nolimits_{m=1}^{K} p_{mi} X_{j-1}^m(t) \tag{15}$$

For $EX2$, we have,

$$\begin{aligned} \lim_{\Delta t\to 0} EX2 = \lambda E(X_j^i(t)) \sum\nolimits_{m=1}^{K} p_{mi} \sum\nolimits_{l=0}^{j-2} X_l^m(t), \\ 1 < j \le L \end{aligned} \tag{16}$$

Similar to (5), we get,

$$\begin{aligned} \lim_{\Delta t\to 0} EX3 = \lambda E(\sum\nolimits_{l=j+1}^{L} X_l^i(t)) \sum\nolimits_{m=1}^{K} p_{mi} X_{j-1}^m(t), \\ 1 \le j \le L \end{aligned} \tag{17}$$

Combining (14)-(17), we have,

$$\begin{aligned} E(\dot{X}_j^i(t)) &= \lambda E(X_{-1}^i(t)) \sum\nolimits_{m=1}^{K} p_{mi} X_{j-1}^m(t) \\ &\quad - \lambda E(X_j^i(t)) \sum\nolimits_{m=1}^{K} p_{mi} \sum\nolimits_{l=0}^{j-2} X_l^m(t) \\ &\quad + \lambda E(\sum\nolimits_{l=j+1}^{L} X_l^i(t)) \sum\nolimits_{m=1}^{K} p_{mi} X_{j-1}^m(t), \\ &\quad 1 < j < L, \quad 1 \le i \le K \end{aligned} \tag{18}$$

When $j = L$, the node having bigger state than j does not exist, so (19) follows.

$$\begin{aligned} X_j^i(t+\Delta t) = X_j^i(t) + \sum\nolimits_{k\in\{X_{-1}^i(t)\}} \varphi_{-1\to j}^k(t, t+\Delta t) \\ - \sum\nolimits_{k\in\{X_j^i(t)\}} \sigma_{j\downarrow}^k(t, t+\Delta t), \quad j = L \end{aligned} \tag{19}$$

In this situation, we can get,

$$\dot{E}(X_j^i(t)) = \lambda E(X_{-1}^i(t)) \sum_{m=1}^{K} p_{mi} X_{j-1}^m(t) - \lambda E(X_j^i(t)) \sum_{m=1}^{K} p_{mi} \sum_{l=0}^{j-2} X_l^m(t), \quad j = L \tag{20}$$

When $j = 1$, the node in state j cannot change to smaller state. In this case, (21) can be got,

$$X_j^i(t+\Delta t) = X_j^i(t) + \sum_{k \in \{X_{-1}^i(t)\}} \varphi_{-1 \to j}^k (t, t+\Delta t) + \sum_{k \in \{X_{>j}^i(t)\}} \rho_{\to j}^k (t, t+\Delta t), \quad j = 1 \tag{21}$$

According to above description, we can easily get,

$$\dot{E}(X_j^i(t)) = \lambda E(X_{-1}^i(t)) \sum_{m=1}^{K} p_{mi} X_{j-1}^m(t) + \lambda E(\sum_{l=j+1}^{L} X_l^i(t)) \sum_{m=1}^{K} p_{mi} X_{j-1}^m(t), \quad j=1 \tag{22}$$

When $j = -1$ or 0, the ODE equations is the same as that in section III-A.

IV. SIMULATION AND NUMERICAL RESULTS

Broadcasting is very useful, for example, the businessman wants to transmit their advertisement to consumers through broadcasting. In this situation, the main metric is to maximize the number of people receiving message (advertisement) when the message is still valid. In this paper, we use the number of nodes receiving message as our metric which is defined as follows,

$$R(t) = \sum_{m=1}^{K} \sum_{j=1}^{L} X_j^m(t) \tag{23}$$

Obviously, symbol $R(t)$ denotes the total number of nodes that carries message (not including the source S which is in state 0) at time t. Therefore, given the maximal message lifetime t, the bigger of $R(t)$, the better of the performance will be. In the rest of this section, we mainly use this metric to denote the performance of the information propagation.

A. SIMULATION

We run several simulations using the Opportunistic Network Environment (ONE) simulator [37]. The first simulation is based on Random Waypoint (RWP) mobility model, which is commonly used in many mobile wireless networks. Here, we select 600 relay nodes and they are evenly divided into 3 communities, so every community has 200 relay nodes. These users move according to the RWP mobility model within a 1000m×1000m terrain according to a scale speed chosen from a uniform distribution from 8m/s to 20m/s. The second simulation is based on a real motion trace from about 2100 operational taxis for about one month in Shanghai city collected by GPS [38]. The location information was recorded at every 40 seconds within an area of 102km^2. We also select 600 relay nodes from the trace and evenly

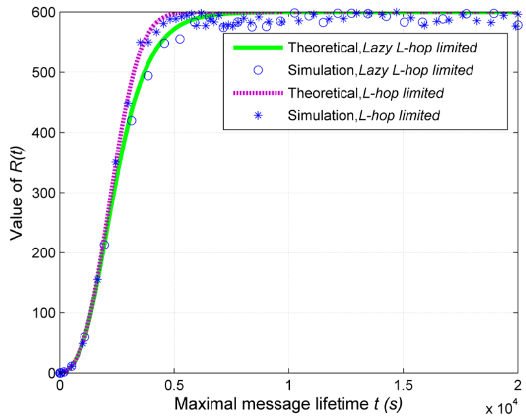

FIGURE 3. Simulation and mathematical results based on the RWP mobility model.

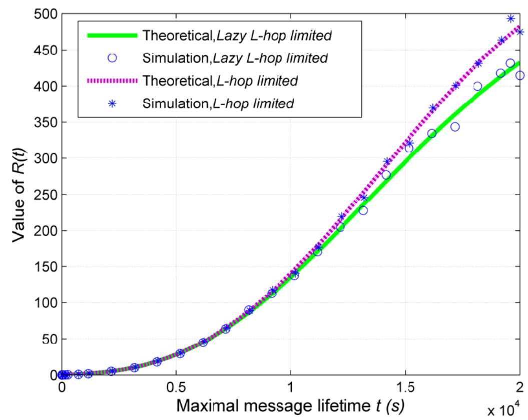

FIGURE 4. Simulation and mathematical results based on the shanghai city motion trace.

divide them into 3 communities. For the theoretical related parameters, there are infinite settings and we cannot carry out the simulation in every setting. For simplicity, we assume that the level of *social selfishness* is 0.2, and level of *individual selfishness* is 0.8. There is also a source node S, and it may be in any community. Because every community has the same number of relay nodes, and these nodes move according to the same mobility model, we can deploy S in any community. In addition, we suppose that the source node S has the same mobility model as the relay nodes.

We set the hop number $L = 3$. The maximal lifetime of the message belongs to the range [0s, 20000s]. The simulation runs 30 times, and the results can be found in Fig.3 and Fig.4. The results show the accuracy of the mathematical model.

In fact, from the results in Fig.3 and Fig.4, we can see that the *Lazy hop-limited flooding* algorithm is only slightly worse than the *hop-limited flooding* algorithm. Numerical results in later section will further demonstrate this phenomenon.

B. PERFORMANCE ANALYSIS WITH NUMERICAL RESULTS

Now, we begin to explore the flooding performance based on different settings. Here, we use the best fitting for the Shanghai city motion trace.

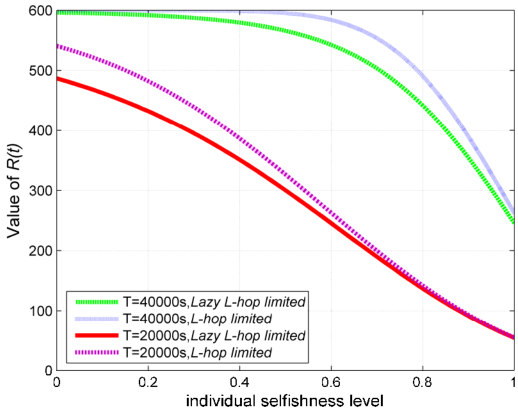

FIGURE 5. Influence of the individual selfishness.

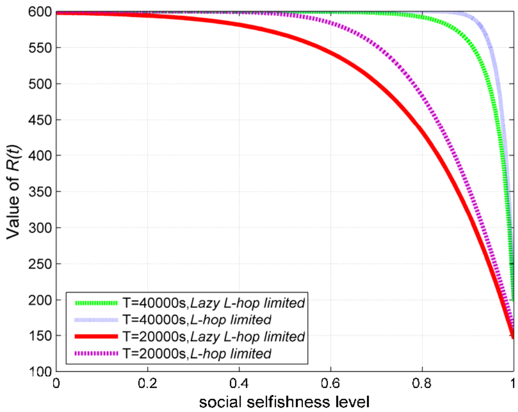

FIGURE 6. Influence of the social selfishness.

First, we study the influence of the individual selfishness, and we set $p_{ij} = 0.2$, $1 \leq i, j \leq K$, $i \neq j$, and $p_{ii} = p$. Obviously, p is a positive constant belonging to [0, 1] and can be seen as the *individual cooperative level*. Therefore, 1-p can be seen as *individual selfishness level*. The maximal lifetime t of the message is set to 20000s and 40000s, respectively. Other settings are the same as that in simulation for Shanghai city motion trace. We can obtain the numerical result in Fig.5.

From Fig.5 we can see that when the maximal message lifetime is bigger, the network is much more robust to the *individual selfishness*. For example, when the maximal lifetime t equals to 40000s, the value of $R(t)$ changes slowly when the level of *individual selfishness* is smaller than 0.4 in both algorithms. However, when $t = 20000$s, $R(t)$ decreases rapidly when the level of *individual selfishness* is increasing. On the other hand, the result also demonstrates that the performance of *L-hop limited flooding* is better than *Lazy L-hop limited flooding*. This is consistent with the results in simulation.

Now, we begin to study the influence of the social selfishness. First, we set the *individual selfishness level* to 0.8, and define $p_{ij} = q$. Similarly, 1-q is the *social selfishness level*. Let it increase from 0 to 1, and we obtain Fig.6.

The result in Fig.6 demonstrates that the influence of the *social selfishness* is similar to *individual selfishness*. However, it seems that the network is more robust to the *social selfishness*. For example, when t = 40000s, the value of $R(t)$

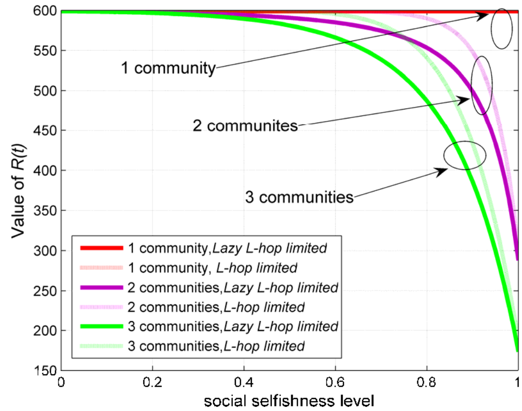

FIGURE 7. Influence of social selfishness when the network has different number of communities.

remains unchanged when the level of individual selfishness is smaller than 0.8. In fact, we think that the influence of selfish behaviors depends on the network structure. Simply speaking, it depends on the number of communities in the network. Therefore, we set the level of *individual selfishness* to be 0 and let t be 20000s. The total number of the relay nodes is 600, and they are uniformly divided into 3 communities. Let the level of *social selfishness* increase from 0 to 1, we can obtain Fig.7.

From the result, we can find that if nodes are selfish, the performance of the flooding algorithm decreases with the number of the communities. However, if the selfish level is small, the influence is very small, too. For example, when level of *social selfishness* is smaller than 0.4, the value of $R(t)$ is nearly the same in any case. On the other hand, Fig.7 also shows that the impact of selfish behaviors is more sensitive when the network has more communities. For example, when the network has only 1 community, the *social selfishness* does not has any impact. However, if there are 2 communities, the performance starts to degenerate when the level of *social selfishness* reaches to 0.4. In addition, when the network has 3 communities, the performance starts to degenerate when the level of *social selfishness* just reaches to 0.3.

Further, we let the level of the *social cooperative* be 0.1. Because nodes are often more willing to help the one in the same community than others, we can assume that the *individual cooperative level* is a little bigger comparing to the *social cooperative level*. Therefore, we let the *individual cooperative level* increase from 0.1 to 1. Other settings are the same as above, and we obtain Fig.8.

From Fig.8, we can find similar phenomenon as Fig.7. That is, if the nodes are selfish, the performance decreases with the number of the communities. Specially, when there are only fewer communities, the flooding policy can tolerant the *individual selfishness* at certain degree. When there is only 1 community, the performance remains unchanged when the level of *individual selfishness* is smaller than 0.3. However, when it is greater than 0.3, the performance of the flooding policy decreases much rapidly. This is different from that

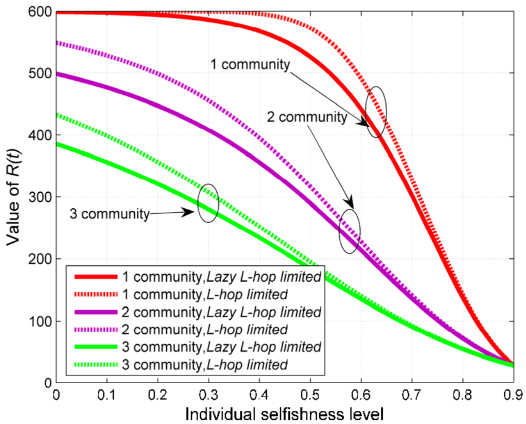

FIGURE 8. Influence of individual selfishness when the network has different number of communities.

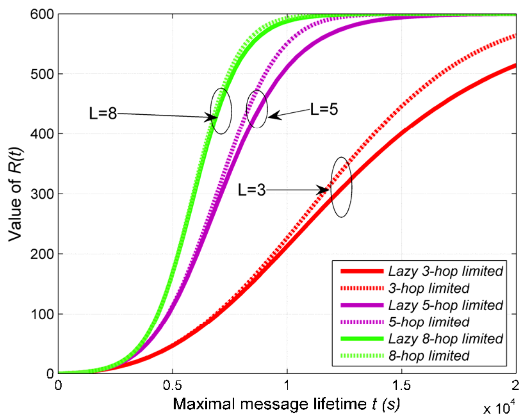

FIGURE 9. Performance with different hop number.

in Fig.7, and this shows that the network is more sensitive to the *individual selfishness*.

In the *hop-limited flooding* algorithms, the value of the hop number may also have certain impact. Our theoretical framework can be used to evaluate its impact, too. First, we evenly divide the 600 relay nodes into 2 communizes. Nodes in the same community help each other with probability 0.8, and nodes in different communities help each other with probability 0.2. Then, we get the mathematical result in Fig.9, when L is set to 3, 5 and 8.

Fig.9 shows that the performance of the hop-limited flooding is increasing with the hop counts. However, the deviation between the *Lazy hop-limited flooding* and *hop-limited flooding* is decreasing with the metric. This demonstrates that when L is bigger, we should adopt the simpler (lazy) algorithm, because it is easy to carry out. In fact, all above results show that the *Lazy hop-limited flooding* is only slightly worse than the more complicated algorithm, so we can say that the *Lazy hop-limited flooding* has some advantages.

In above results, we assume that every community has the same number of relay nodes and these nodes have the same selfish behaviors. Under these assumptions, the location of the source S does not have any impact. In real world, the number of relay nodes in every community is different and

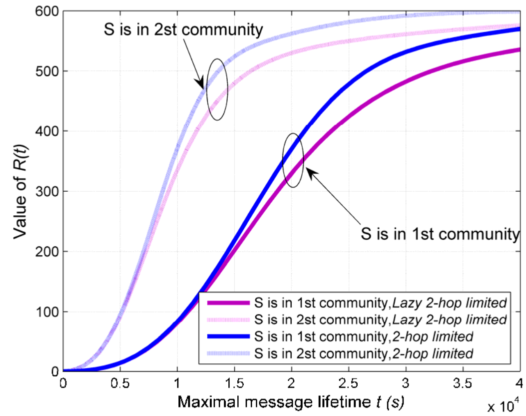

FIGURE 10. Performance when the source S is in different locations.

nodes may also have different selfish level. In this situation, the location of S may have certain impact on the flooding performance. To explore its impact, we assume that there are 2 communities. The first community has 100 relay nodes, and the second community has 500 relay nodes. Further, we assume that level of *individual selfishness* in the first community equals to 0.8, but level of individual selfishness in the second community equals to 0.2. The level of *social selfishness* for any node is 0.9. Let L = 2 and we can obtain Fig.10.

From the result in Fig.10 we can see that the location of the source really has certain impact on the flooding performance when the communities are heterogeneous. The deviation between the performances when S is in different locations is big. For example, the deviation for the *Lazy 2-hop limited flooding* is about 142.86% when the maximal message lifetime t = 15000s. This deviation is much bigger than that between the *Lazy hop-limited flooding* and *hop-limited flooding* algorithm. Therefore, this result further shows that the *Lazy hop-limited flooding* is only slightly worse than the *hop-limited flooding algorithm.*

V. CONCLUSIONS

The work of this paper mainly studies the influence of two kinds of selfish behaviors on the performance of hop-limited flooding in DTN. We use the ODE method to model the message spreading process. The mathematical model is checked based on several simulations. Through extensive numerical results, we find many interesting characteristics. For example, the influence of the selfishness closely depends on the network structure. There are several possible extensions in the future work, two of them are the situation where there exist multiple messages to be forwarded and the situation where the message is divided into multiple frames.

If implementing these policies in the practical case, each node should maintain a head that contains the community ID and the state of the node. When two nodes encounter, they first exchange the head, then they change their state and transmit the message according to hop-limited routing policy. However, the node may transmit a fake state and lead to negative influence on the performance. Therefore, it is very important to design corresponding incentive policy to encourage the nodes to work in a cooperative and truthful way, which is left as our future work.

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