The Impact of Node Selfishness on Multicasting in Delay Tolerant Networks

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***Abstract*—Due to the uncertainty of transmission opportunities between mobile nodes, delay tolerant networks (DTNs) exploit the opportunistic forwarding mechanism. This mechanism requires nodes to forward messages in a cooperative and selfish way. However, in the real word, most of the nodes exhibit selfish behaviors, such as individual and social selfishness. In this paper, we are the first to investigate how the selfish behaviors of nodes affect the performance of DTN multicast. We consider two typical multicast relaying schemes, namely, two-hop relaying and epidemic relaying, and study their performance in terms of average message transmission delay and transmission cost. Specifically, we model the message delivery process under selfish behaviors by a 3-D continuous time Markov chain; under this model, we derive closed-form formulas for the message transmission delay and cost. Then, we evaluate the accuracy of the proposed Markov chain model by comparing the theoretical results with the simulation results obtained by simulating the message dissemination under both two-hop and epidemic relaying with different network sizes and mobility models. Our study shows that different selfish behaviors may have different impacts on different performance metrics. In addition, selfish behaviors influence epidemic relaying more than two-hop relaying. Furthermore, our results show that the performance of multicast with selfish nodes depends on the multicast group size.**

***Index Terms*—Delay tolerant networks (DTNs), multicast, node selfishness, performance evaluation.**

I. Introduction

To PROVIDE communication service in highly challenged wireless networks where there only exists intermittent connectivity, delay tolerant networks (DTNs) [1], [2] were proposed. In DTNs, there are no end-to-end paths between the communication sources and destinations due to sparse node density and unpredictable node mobility. Examples of such networks include vehicular ad hoc networks [3], deep-space interplanetary networks [4], underwater networks [1], military networks [5], etc. In such kind of networks, traditional ad hoc routing protocols, which rely on the end-to-end paths [6], fail to work [1]. For example, in vehicular-based DTN, the nodes are vehicles, and they move very quickly. Therefore, the network is highly mobile and frequently disconnected, and it is unrealistic to maintain the end-to-end paths between any communication source and destination pair. Thus, a new routing mechanism, which is known as the store-carry-and-forward paradigm [7], [8], is proposed to provide communication. In this routing mechanism, node mobility and intermittent connectivity are exploited to let mobile nodes serve as relays to carry messages and forward them upon probabilistic contacts around the networks [7], [9].

Obviously, this new routing mechanism requires nodes to forward messages in a cooperative and selfless way [10]. For example, when the next hop is not immediately available for some node to forward a message, the node should utilize its own limited buffer to store the message, carry the message along the movement, and forward the message when it moves within the transmission range of other nodes that help to deliver this message further. However, in the real world, most of the nodes exhibit noncooperative behaviors [11], [12], e.g., a node may not be willing to store messages in its buffer or relay messages on behalf of others to conserve limited buffer and power resources. That is to say, nodes are selfish in the message forwarding and relaying process. For example, in mobile social networks, people sharing similar interests form a community via mobile phones [13]. From the perspective of an individual node, the node is unwilling to relay and store messages for others to conserve limited buffer and power resources [14]. While from the perspective of a community, the members are more willing to receive and forward messages for the nodes in the same community but are less interested in receiving and forwarding messages for the nodes outside their community [13]. These two types of selfishness are called individual selfishness and social selfishness, respectively [10].

This paper is intended to study the effect of both individual and social selfishness on the multicast performance. To the best of our knowledge, only a few existing works [10], [15]–[17] deal with node selfishness issues in DTN, and most of the current works either neglect the node selfishness or only consider the individual selfishness [10], [17]. Moreover, all these works focus on forwarding data to a single destination.

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However, multicast is more efficient for data transmission to a group of users. Recent works [18]–[20] find that it is efficient to use the DTN communication mechanism to provide multicast services, i.e., providing update information such as news, weather reports, road and traffic congestion, and stock prices [18], [21] to a group of users. In these multicast applications, a source dynamically transmits data to its subscribers, and a subscriber may relay the most up-to-date content to others when an opportunistic contact occurs between them. Obviously, multicast performance is prone to node selfish behaviors. However, it is difficult to model and analyze the performance of multicast under node selfishness.

In this paper, we focus on evaluating the impact of node selfishness on the performance of multicast in DTN. To our best knowledge, we are the first to investigate the effect of selfish behaviors on the DTN multicast performance. We consider the impact of both individual and social selfishness on two multicast relaying schemes, namely, two-hop relaying and epidemic relaying. In the case of individual selfishness, we characterize it by 1) the probability that a node holding a message does not forward the message and 2) the probability that a node not holding the message does not copy the message from other nodes. In the case of social selfishness, we characterize it by 1) the probability that a node (say *Node A*) transmits messages for nodes in the community to which Node A belongs and 2) the probability that the node transmits messages for nodes in the community to which Node A does not belong. By modeling the message dissemination process among the selfish nodes as a 3-D continuous-time Markov chain, we derive the system performance of both message transmission delay and transmission cost. Then, we investigate the multicast performance and analyze the tradeoff between performance and cost under different selfish behaviors and different relaying schemes by extensive numerical study. Our results show that different types of individual selfishness have different effects on the performance of message transmission delay and cost. For example, not copying the message increases the delay but reduces the cost, while not forwarding the message increases both delay and cost. In contrast, social selfishness has a different effect from that of individual selfishness of not forwarding message; it increases the message delivery delay and at the same time decreases the delivery cost, which demonstrates that DTN multicast is robust to social selfishness. Regarding the robustness of different relaying schemes, we find that the node selfish behaviors have more impact on the performance of epidemic relaying than that of two-hop relaying. Moreover, our results show that the multicast performance measures, i.e., message transmission delay and cost, depend much on the number of multicast destinations when the system contains nodes that behave selfishly.

The rest of this paper is organized as follows: After presenting the related work in Section II, we describe the system model, give the analysis framework, and derive the system performance of message transmission delay and cost in Section III. In Section IV, we validate the accuracy of our system model by simulation. Then, we describe the settings for performance evaluation and present numerical results in Section V. Finally, we conclude this paper in Section VI.

II. Related Work

In the past few years, many routing and forwarding algorithms have been proposed to improve the performance of DTN unicast routing. Epidemic routing [22] is a flooding-based protocol, which replicates messages at every contact. A number of approaches have been proposed to reduce its overhead [8], [23]. Among them, there are opportunistic-forwarding (or probabilistic-forwarding)-based approaches that rely on probability metrics such as time elapsed since last encounter [24], social similarity [25], geometric distance [26], and so on. These routing schemes try to achieve short message delivery delay and relatively low transmission cost. However, there is a tradeoff between them. Generally speaking, short delivery delay is obtained at the expense of more cost. Therefore, it is important to accurately evaluate the performance of these routing schemes to show their strengths and limitations. Some works use simulation methods [7], [27], but recently, theoretical analysis frameworks, such as Markov models [17] and the ordinary differential equation model [28], have also been used to evaluate the performance. In this paper, we use a more sophisticated Markov model to evaluate the impact of selfishness on the performance of DTN multicast.

Works on routing for the DTN multicast include [29]–[32]. Zhao *et al.* [29] propose some new semantic models to capture the unique characteristic of frequent partitioning in DTN and develop several multicast algorithms with different strategies. Lee *et al.* [30] study the scalability property of DTN multicast routing and propose RelayCast to improve the throughput bound of multicast by exploiting node mobility. Gao *et al.* [31] study the multicast problem from the social network perspective. By using the node centrality and social community property, they formulate the relay selections for multicast as a unified knapsack problem and demonstrate the efficiency of the proposed schemes by simulation results. Different from these works that focus on designing routing mechanisms, Abdulla and Simon [32] study the performance of multicast by simulation. However, all these works assume that nodes would be cooperative in message transmission but do not consider the nodes' selfishness behaviors. Therefore, it is important for us to evaluate the impact of selfish behaviors on the performance of DTN multicast.

In terms of node selfishness, Panagakis *et al.* [15] evaluate the DTN routing performance under different levels of cooperation through simulation. Resta and Santi [16] present a theoretical framework to study the effects of different degrees of node cooperation. However, the proposed framework only allows performance evaluation in terms of message transmission delay but does not allow the study of the tradeoff between transmission delay and cost caused by noncooperative behaviors. Shevade *et al.* [11] consider the individually selfish behaviors of users and propose a robust and practical incentive mechanism to stimulate selfish nodes to forward messages in the system. Li *et al.* [10] consider the social selfishness and propose a social selfishness aware routing algorithm to allow user selfishness behaviors and provide better routing performance in an efficient way. Karaliopoulos [17] evaluates the impact of individual selfishness on DTN unicast routing by only considering the message transmission delay, and Li *et al.* [33] evaluate the impact of social selfishness on DTN unicast routing by considering the delay and cost. From these related works, we can see that they study the problem of DTN unicast routing, and most of them either neglect the node selfishness or only consider the individual selfishness [10], [11], [17]. Our work aims to study how both the individual and social selfishness affect the performance of message transmission in DTN multicast.

III. System Model and Performance Analysis

A. System Model

We model a DTN as a set of wireless mobile nodes, which are denoted by V, and the number of nodes is $|V| = 1 + L + M + N$. Among them, there are a source node, L destination nodes, and $M + N$ relay nodes. Considering the social selfishness behaviors of nodes we study in this paper, we should model the community property among nodes. Actually, there are two types of community models: 1) overlapping and 2) nonoverlapping [34]. However, for more efficient analysis, we limit our community model to a nonoverlapping model, in which one node belongs to at most one community. We cluster the nodes in a socially selfish DTN into two communities denoted by V_1 and V_2, where $\{a_1, a_2, \ldots, a_M\} \subseteq V_1$, and $\{b_1, b_2, \ldots, b_N\} \subseteq V_2$. At the same time, to evaluate the impact of individual selfishness, we let the nodes $\{b_1, b_2, \ldots, b_N\}$ be individual selfishness nodes, whereas nodes $\{a_1, a_2, \ldots, a_M\}$ are not individually selfish. With respect to the source s_1 and destination nodes $\{d_1, d_2, \ldots, d_L\}$, we will study two cases: 1) $V_1 = \{a_1, a_2, \ldots, a_M, s_1, d_1, d_2, \ldots, d_L\}$ and $V_2 = \{b_1, b_2, \ldots, b_N\}$ and 2) $V_1 = \{a_1, a_2, \ldots, a_M\}$ and $V_2 = \{b_1, b_2, \ldots, b_N, s_1, d_1, d_2, \ldots, d_L\}$.

In this paper, we consider one message transmission from the multicast source to the destinations and investigate the performance of average message transmission delay and transmission cost. Since the density of the nodes is sparse in a DTN environment, they can communicate only when they move into the transmission range of each other, which means a communication contact. We assume that the occurrence of contacts between two nodes follows a Poisson distribution, which is used by [31]. Consequently, the intercontact time between two nodes follows an exponential distribution with the parameter denoted by λ. About the Poisson contact rate, there is some concern with regard to its applicability since it may be not valid in part of the intercontact time distribution under specific assumptions in the mobility patterns. There is evidence that this holds. For example, recent work [35] shows that the intercontact time is a truncated power law with exponential decay appearing in its tail after some cutoff point. However, generally, the intercontact time follows the exponential distribution in many cases. For example, [36] and [37] model the intercontact time between vehicles, and [31] models the intercontact time of each individual human. They reveal the exponential distribution of intercontact time between nodes by analyzing a large number of real mobility traces. That is to say, the exponential intercontact time holds for mobility behaviors of both the human and vehicles [31], [36], which are the most typical nodes in DTNs of mobile social networks and vehicle ad hoc networks, respectively [2]. Furthermore, it enables the theoretical analysis by using the continuous Markov model. Therefore, from these aspects, we model it as an exponential distribution. In our model, nodes may belong to different communities, and their contact rate may vary with their community relationships. Considering the quite different intercontact time distributions for intercommunity and intracommunity reported in [38], we set the contact rate of the nodes that are inside the same community to be λ_i and set the contact rate of the nodes with others outside their community to be λ_o.

Upon contact that may result in message transmission, the node selfish behaviors, including social selfishness and individual selfishness, would take effect. In terms of individual selfishness, a selfish node already having the message may not forward it to another node, which does not have the message, or a node that does not have the message may not be willing to receive/copy it. We consider these two types of individual selfishness: the relay node does not forward the message to another node without the message with probability $p_{nf} \in [0, 1]$, or it does not copy the message from others with the probability $p_{nc} \in [0, 1]$ when it does not have the message. Consequently, p_{nf} and p_{nc} refer to individual selfishness levels. In terms of social selfishness, the probability that two nodes successfully transmit a message depends on their community relationship. This means that the probabilities for intercommunity and intracommunity message transmission are different. Therefore, we assume that if two nodes are in the same community, then the message is forwarded with probability p_i. Otherwise, the probability is p_o. In general, $p_i > p_o$ due to the nature of social selfishness. Since the source and destination nodes will not behave selfishly in real networks, we only assume that the relay nodes have such selfish behaviors. The source node will always try to send the message to other nodes, and the destination nodes will always try to receive the message from other nodes; in other words, $p_{nf} = 0$ for the source and $p_{nc} = 0$ for destinations. Therefore, if the source meets one of the destinations, then the message will always be transmitted; on the other hand, if the source encounters a relay node or a relay node encounters the destinations, then the message may not be transmitted as a result of the selfishness of this relay node.

Regarding DTN multicast relaying algorithms, we consider two typical schemes, i.e., two-hop relaying and epidemic relaying, which are described as follows.

1) Two-hop relaying: In two-hop relaying, the source node can send the message to any other node, but the relay nodes can only forward it to the multicast destinations. The destination nodes will not help to forward the message. Two-hop relaying aims at limiting the number of message transmissions.
2) Epidemic relaying: In epidemic relaying, packets arrived at intermediate nodes are forwarded to all neighbors of the nodes, but the destination nodes will not help to forward the message. There are no constraints on the number of message copies in the network, and the messages are transmitted in a flooding way.

Considering the message transmission process in the multicasting under the node selfish behaviors, we can model it by a 3-D continuous time Markov chain with state $(l(t), m(t), n(t))_{t\geq 0}$, where $l(t)$ represents the number of destination nodes that have received the message at time t, and $m(t)$ $(or\ n(t))$ represents the number of relay nodes holding the message in community V_1 $(or\ V_2)$. At the beginning of the message transmission, only the source node has the message copy. Then, when it encounters other nodes, a message transmission may occur. Consequently, $n(t)$, $m(t)$, or $l(t)$ may increase by one, depending on the community to which the node belongs. Therefore, we can say that this Markov chain starts with state (0, 0, 0) and has $S_1 = L(N+1)(M+1)$ transient states. In the transient state $(L-1, m(t), n(t))$, the message may be forwarded to the last destination, which means that the absorbing state, which is denoted by state $(L, m(t), n(t))$, and the number of absorbing states are $S_2 = (N+1)(M+1)$. Consequently, the number of total states is $S_1 + S_2$. Thus, we can obtain its generator matrix $\mathbf{Q}$ by the following form:

$$\mathbf{Q} = \begin{pmatrix} \mathbf{T} & \mathbf{R} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \tag{1}$$

where the submatrix $\mathbf{T}$ is a $S_1 \times S_1$ matrix with element $T_{i,j}$ denoting the transition rate from transient state (i) to state (j), and R is a $S_1 \times S_2$ matrix with element $R_{i,k}$ denoting the transition rate from transient state (i) to the absorbing state (k). The left $\mathbf{0}$ is a $S_2 \times S_1$ matrix with all the elements 0 meaning the zero transition rates from the absorbing state to the transient states. The right $\mathbf{0}$ is a $S_2 \times S_2$ matrix representing the zero transition rates between the absorbing states. According to the different multicast relaying schemes controlling the message forwarding, we obtain the transition rate $\{q_{i,j}\}$ from state (i) to state (j) in the following two sections.

1) Two-Hop Relaying: In two-hop relaying, only the source node can send the message to any other node, whereas the relay nodes can only forward it to the destinations, and the destinations will not forward anything. We consider the message transmission process when the system is in the transient state (l, m, n). In this state, there are l destination nodes that have already received the message, and there are m and n relay nodes, which have a copy of the message, in the communities V_1 and V_2, respectively. When one of the nodes without the message encounters the source node, the system state may change if the message is transmitted successfully. If the node is the relay node in community V_1 (or V_2), then the system state changes to $(l, m+1, n)$ (or $(l, m, n+1)$), and if the node is a destination node, then the state turns to $(l+1, m, n)$.

Now, we derive the transition rate $\{q_{i,j}\}$ of the case that the source and destination nodes are in community V_1. According to the message forwarding and copying behaviors influenced by the selfishness we defined, we know that the transition rate from state (l, m, n) to state $(l, m+1, n)$ is $(M-m)\lambda_i p_i$; this is because there are $M-m$ relay nodes in V_1 that may receive the message with probability p_i, only the source node can forward the message to them, and the communication rate of each pair is λ_i. Similarly, the transition rate to state $(l, m, n+1)$ is $(N-n)\lambda_o p_o(1-p_{nc})$, and the transition rate to state $(l+1, m, n)$ is $(L-l)(\lambda_i + m\lambda_i p_i + n\lambda_o p_o(1-p_{nf}))$. Therefore, the transition rates can be given as follows (with $\mathbf{Q}_{t1}$ denoting $\mathbf{Q}$ in this situation):

$$\begin{cases} Q_{t1}\{(l,m+1,n)|(l,m,n)\} = (M-m)\lambda_i p_i \\ \qquad \text{for } n \in [0,N], m \in [0,m-1], l \in [0,L-1] \\ Q_{t1}\{(l,m,n+1)|(l,m,n)\} = (N-n)\lambda_o p_o(1-p_{nc}) \\ \qquad \text{for } n \in [0,N-1], m \in [0,m], l \in [0,L-1] \\ Q_{t1}\{(l+1,m,n)|(l,m,n)\} = (L-l) \\ \qquad \times (\lambda_i + m\lambda_i p_i + n\lambda_o p_o(1-p_{nf})) \\ \qquad \text{for } n \in [0,N], m \in [0,m], l \in [0,L-1] \\ Q_{t1}\{(l,m,n)|(l,m,n)\} = -Q_{t1}\{(l,m+1,n)|(l,m,n)\} \\ \qquad - Q_{t1}\{(l,m,n+1)|(l,m,n)\} \\ \qquad - Q_{t1}\{(l+1,m,n)|(l,m,n)\} \\ \qquad \text{for } n \in [0,N], m \in [0,m], l \in [0,L-1]. \end{cases}$$

Similar to the foregoing derivation, we now consider the transition rate $\{q_{i,j}\}$ of the case that the source and destination nodes are in community V_2, and they can be expressed as follows (with $\mathbf{Q}_{t2}$ denoting $\mathbf{Q}$ in this situation):

$$\begin{cases} Q_{t2}\{(l,m+1,n)|(l,m,n)\} = (M-m)\lambda_o p_o \\ \qquad \text{for } n \in [0,N], m \in [0,m-1], l \in [0,L-1] \\ Q_{t2}\{(l,m,n+1)|(l,m,n)\} = (N-n)\lambda_i p_i(1-p_{nc}) \\ \qquad \text{for } n \in [0,N-1], m \in [0,m], l \in [0,L-1] \\ Q_{t2}\{(l+1,m,n)|(l,m,n)\} = (L-l) \\ \qquad \times (\lambda_i + m\lambda_o p_o + n\lambda_i p_i(1-p_{nf})) \\ \qquad \text{for } n \in [0,N], m \in [0,m], l \in [0,L-1] \\ Q_{t2}\{(l,m,n)|(l,m,n)\} = -Q_{t2}\{(l,m+1,n)|(l,m,n)\} \\ \qquad - Q_{t2}\{(l,m,n+1)|(l,m,n)\} \\ \qquad - Q_{t2}\{(l+1,m,n)|(l,m,n)\} \\ \qquad \text{for } n \in [0,N], m \in [0,m], l \in [0,L-1]. \end{cases}$$

2) Epidemic Relaying: In epidemic relaying, the message arriving at the intermediate nodes is forwarded to all of the nodes' neighbors in contact. In epidemic relaying, all the nodes except the destinations can forward the message to other nodes, which is different from two-hop relaying.

Similar to the analysis in two-hop relaying, we first consider the case that the source and destination nodes are in community V_1 and have the transition rates given by the following expressions (with $\mathbf{Q}_{e1}$ denoting $\mathbf{Q}$ in this situation):

$$\begin{cases} Q_{e1}\{(l,m+1,n)|(l,m,n)\} = (M-m) \\ \qquad \times ((m+1)\lambda_i p_i + n\lambda_o p_o(1-p_{nf})) \\ \qquad \text{for } n \in [0,N], m \in [0,m-1], l \in [0,L-1] \\ Q_{e1}\{(l,m,n+1)|(l,m,n)\} = (N-n)(1-p_{nc}) \\ \qquad \times ((m+1)\lambda_o p_o + n\lambda_i p_i(1-p_{nf})) \\ \qquad \text{for } n \in [0,N-1], m \in [0,m], l \in [0,L-1] \\ Q_{e1}\{(l+1,m,n)|(l,m,n)\} = (L-l) \\ \qquad \times (\lambda_i + m\lambda_i p_i + n\lambda_o p_o(1-p_{nf})) \\ \qquad \text{for } n \in [0,N], m \in [0,m], l \in [0,L-1] \\ Q_{e1}\{(l,m,n)|(l,m,n)\} = -Q_{e1}\{(l,m+1,n)|(l,m,n)\} \\ \qquad - Q_{e1}\{(l,m,n+1)|(l,m,n)\} \\ \qquad - Q_{e1}\{(l+1,m,n)|(l,m,n)\} \\ \qquad \text{for } n \in [0,N], m \in [0,m], l \in [0,L-1]. \end{cases}$$

At the same time, when the source and destination are in the community V_2, we can have (with $\mathbf{Q}_{e2}$ denoting $\mathbf{Q}$ in this situation)

$$\begin{cases} Q_{e2}\left\{(l,m+1,n)|(l,m,n)\right\} = (M-m) \\ \qquad \times\left(\lambda_o p_o + m\lambda_i p_i + n\lambda_o p_o(1-p_{nf})\right) \\ \qquad \text{for } n\in[0,N], m\in[0,m-1], l\in[0,L-1] \\ Q_{e2}\left\{(l,m,n+1)|(l,m,n)\right\} = (N-n)(1-p_{nc}) \\ \qquad \times\left(\lambda_i p_i + quadm\lambda_o p_o + n\lambda_i p_i(1-p_{nf})\right) \\ \qquad \text{for } n\in[0,N-1], m\in[0,m], l\in[0,L-1] \\ Q_{e2}\left\{(l+1,m,n)|(l,m,n)\right\} = (L-l) \\ \qquad \times\left(\lambda_i + m\lambda_o p_o + n\lambda_i p_i(1-p_{nf})\right) \\ \qquad \text{for } n\in[0,N], m\in[0,m], l\in[0,L-1] \\ Q_{e2}\left\{(l,m,n)|(l,m,n)\right\} = -Q_{e2}\left\{(l,m+1,n)|(l,m,n)\right\} \\ \qquad -Q_{e2}\left\{(l,m,n+1)|(l,m,n)\right\} \\ \qquad -Q_{e2}\left\{(l+1,m,n)|(l,m,n)\right\} \\ \qquad \text{for } n\in[0,N], m\in[0,m], l\in[0,L-1]. \end{cases}$$

B. Performance Analysis

Based on the Markov chain model, we consider two important system performance metrics, i.e., message transmission delay and message transmission cost, which are defined as follows

1) Message transmission delay: the average time needed to finish transmitting the message to all multicast destinations, in other words, the expectation of the time elapse from the start until the last destination receives the message;
2) Message transmission cost: the average number of times that the message is transmitted until it has been forwarded to all the multicast destinations.

Regarding the message delivery cost, we only consider the minimum cost needed to deliver a message to all the destinations. Therefore, our defined transmission cost is just a portion of the actual transmission cost if no mechanism is employed to stop the propagation when all the destinations have received the message. However, if there is some mechanism such as that in [22] and [24] to notify all the nodes in the network when the message has reached all the destinations, then our defined transmission cost is equal to the actual transmission cost.

1) Message Transmission Delay: According to the transition matrix $\mathbf{T}$ in (1) and [17], we have the expectation of the message transmission delay, which is denoted by D_t, as follows:

$$D_t = E\{D\} = \mathbf{v}_1 \cdot (-\mathbf{T}^{-1}) \cdot \mathbf{v}_2 \tag{2}$$

where D is a random variable denoting the transmission delay for each sample, $\mathbf{v}_1 = [1, 0, \ldots, 0]$ is a $1 \times S_1$ vector denoting the initial state probability vector, and $\mathbf{v}_2 = [1, 1, \ldots, 1]^{\mathrm{T}}$ is a $S_1 \times 1$ all-one vector.

2) Message Transmission Cost: Similar to [33], to obtain the message transmission cost, we need to know the transition probability that the transient state $(i)_{i\in[1,S_1]}$ transitions to the absorbing state $(j)_{j\in[S_1+1,S_1+S_2]}$. For this purpose, we consider the corresponding embedded Markov chain, whose single-step transition probability matrix is denoted by $\mathbf{P}$. Its element $p_{i,j}$ is expressed as follows:

$$p_{i,j} = \begin{cases} -q_{i,j}/q_{i,i}, & j \neq i \\ 0, & j = i. \end{cases}$$

Consequently, the one-step transition probability that state (0, 0, 0) transitions to the absorbing states, which is denoted by $\hat{p}(1)$, can be calculated as $\hat{p}(1) = \sum_{k=S_1+1}^{S_1+S_2} p_{1,k}$. Then, $\mathbf{P}^2$ is the two-step transition probability matrix, and the probability that state (0, 0, 0) transitions to the absorbing states via transition of no more than two steps is $\hat{p}(2) = \sum_{k=S_1+1}^{S_1+S_2} \mathbf{P}_{1,k}^2$, where $\mathbf{P}_{1,k}^2$ denotes the $(1, k)$ element of matrix $\mathbf{P}^2$; thus, the transition probability that state (0, 0, 0) transitions to absorbing states via exactly two steps is $(\hat{p}(2) - \hat{p}(1))$. Similarly, $\mathbf{P}^i$ is the i step transition probability matrix, and $(\hat{p}(i) - \hat{p}(i-1))$ shows the probability that the Markov chain arrives at the absorbing states via exactly i steps. Furthermore, after each transmission, at least one more node will get the message, leading to the increase of $l + m + n$; thus, there are at most $L + M + N$ steps before arriving at the absorbing states and $\hat{p}(L + M + N) = 1$. Therefore, the expectation of the message transmission cost, which is denoted by C_t, is given as

$$\begin{aligned} C_t = E\{C\} &= \hat{p}(1) + \sum_{i=2}^{L+M+N} i \cdot (\hat{p}(i) - \hat{p}(i-1)) \\ &= L + M + N - \sum_{i=1}^{L+M+N-1} \hat{p}(i) \\ &= L + M + N - \sum_{i=1}^{L+M+N-1} \sum_{k=S_1+1}^{S_1+S_2} \mathbf{P}_{1,k}^i \end{aligned} \tag{3}$$

where C is the random variable denoting the transmission cost for each sample, and $\mathbf{P}_{1,k}^i$ denotes the $(1, k)$ element of matrix $\mathbf{P}^i$.

IV. Model Validation

In this section, we evaluate the accuracy of our model by comparing the theoretical results obtained based on our model with the simulation results, which are obtained by simulating the message dissemination under two-hop and epidemic relaying with different network sizes and mobility models. At the same time, we further investigate the impact of the assumed model of exponential intercontact time on the accuracy of theoretical results.

A. Evaluation Settings

We conduct simulation under different numbers of mobile nodes and different mobility models and use both synthetic mobility models and real-world-based scenarios, including Poisson contact rate controlled mobility, random waypoint (RWP), and a map-driven DTN with pedestrians and transportation systems in the opportunistic network environment (ONE) simulator [39]. In the synthetic model of RWP, the simulation area is set to be 500×5000 m^2, and the nodes' speed varies from

0.6 to 1.4 m/s. In the map-driven DTN model, the nodes move along the streets on an imported map of downtown Helsinki, Finland. The size of the map is 4500×3400 m^2, and the nodes' transmission range is 100 m. About 15% of the nodes are configured to follow the predefined routes with speed uniformly distributed in the range of [2, 5] m/s, and other settings are default in the ONE simulator for tram vehicle. The remaining nodes are divided into three groups. For each group, there are points of interest (POIs), and we assign a different probability for picking the next node from a particular group of POIs to simulate the phenomenon that people visit certain areas of a place more frequently than other areas based on feature, such as age and profession. Other settings are default in the ONE simulator.

For our system model related parameters, we set $L = 5$, $p_{nf} = p_{nc}$, $p_i = p_o$, and $\lambda_i = \lambda_o$. Without loss of generality, we set $p_{nf} = 0$ and then vary p_i and the total number of nodes $|V|$ since our goal was to verify the accuracy of the theoretical model. First, we use the Poisson contact model to simulate the system with different network sizes to validate the scalability of our model and then use different mobility models to demonstrate its accuracy in various environments.

B. Results

We first simulate the network with different network sizes $|V|$ of 100, 200, and 300, where the Poisson process with $\lambda_i = \lambda_o = 3.71 \times 10^{-6}$ s^{-1} is used to generate node contact events. This value of λ_i and λ_o is obtained from the vehicle model, which is based on real motion traces from about 2100 operational taxis for about one month in Shanghai city collected by GPS [40]. To establish an accurate mobility model from the traces, the authors of [37] perform least-square fitting to identify the exponential parameter and find that the intercontact time is well approximated by the exponential distribution of $P\{X > t\} = e^{-3.71\times10^{-6}t}$ $(t > 0)$. Therefore, here, we set the parameter $\lambda_i = \lambda_o = 3.71 \times 10^{-6}$ s^{-1}. At the beginning of the simulation, one of the nodes is randomly chosen to be the source, which wants to transmit a message to L randomly chosen destinations; then, we simulate the message dissemination using the contact events generated. What we measure is the average message transmission delay. The theoretical and simulation results obtained for the delay of two-hop and epidemic relaying are plotted in Figs. 1 and 2. As expected, the message transmission delay computed from our model agrees with that obtained by the simulation of both two-hop and epidemic relaying, indicating the accuracy of our model.

We then use synthetic mobility models, RWP, and a map-driven DTN model (MAP) with pedestrians and transportation systems in the ONE simulator [39]. We set $|V| = 200$ for RWP and $|V| = 126$ for MAP, randomly choose one of the nodes as the source and L nodes as the destinations, and use the default mobility model settings in the ONE simulator. The results obtained for two-hop and epidemic relaying are shown in Figs. 3 and 4, where it can be seen that the average deviation of the theoretical results from the simulated results is small. Specifically, for two-hop relaying, the deviation is 3.3% for RWP and 15.7% for MAP; hence, the average deviation is 9.5%. For epidemic relaying, the average deviation is 16.9%. This demonstrates the accuracy of our Markov model to evaluate the performance of the DTN multicasting system.

We have noted that the results obtained in the RWP model are more accurate than those in the MAP model, which is

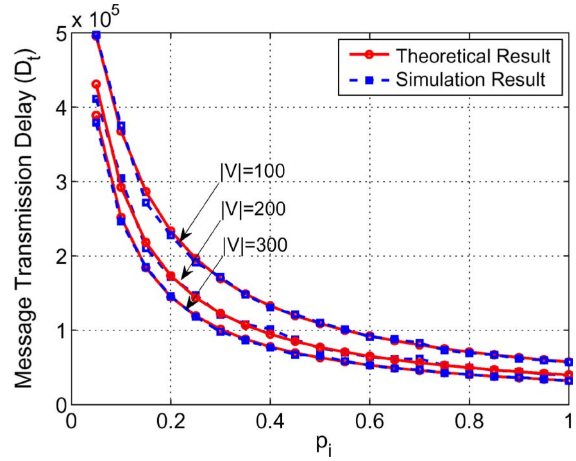

Fig. 1. Theoretical and simulation result comparison in terms of the message transmission delay of two-hop relaying assuming the Poisson contact process and with different network sizes.

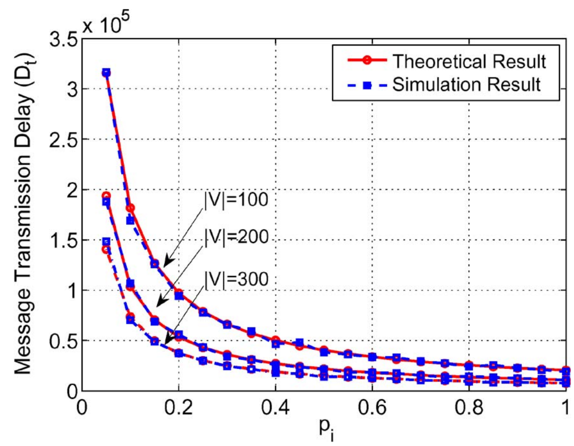

Fig. 2. Theoretical and simulation result comparison in terms of the message transmission delay of epidemic relaying assuming the Poisson contact process and with different network sizes.

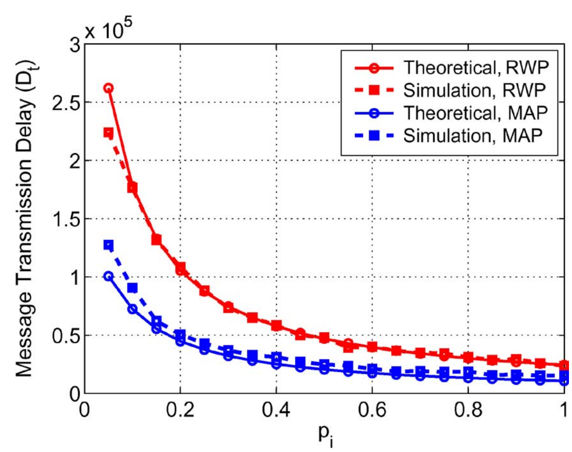

Fig. 3. Theoretical and simulation result comparison in terms of the message transmission delay using two-hop relaying for different mobility networks.

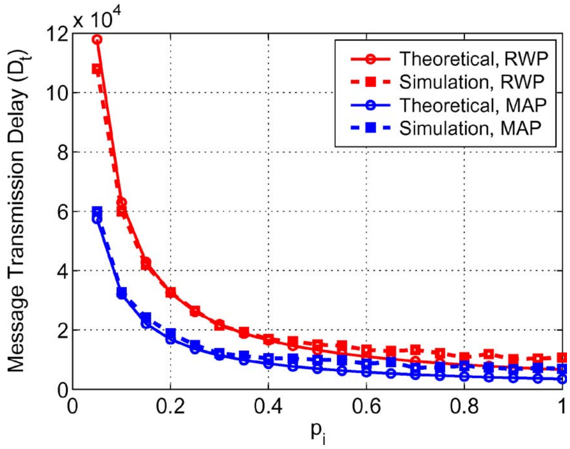

Fig. 4. Theoretical and simulation result comparison in terms of the message transmission delay using epidemic relaying for different mobility networks.

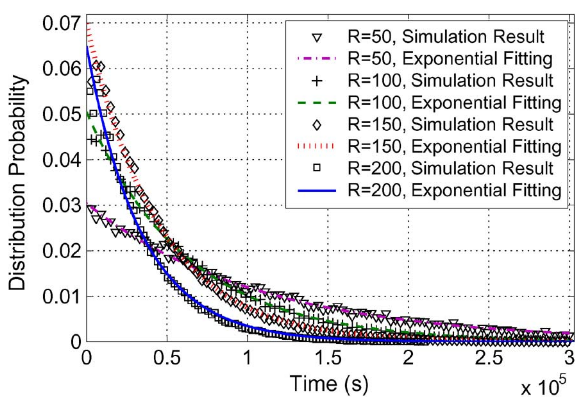

Fig. 5. Results of using exponential distribution to fit the simulation data of intercontact time obtained in the RWP model with different transmission ranges R.

mainly caused by different node mobility settings. Now, we investigate the impact of the assumed exponential intercontact time on the accuracy of system performance. Different mobility models may induce some variations in intercontact time distribution. Therefore, we first investigate the intercontact time that is generated by the RWP and MAP models. To know the influence of the transmission range R on the intercontact time distribution, we set R as 50, 100, 150, and 200 m. Under different transmission ranges, we obtain the simulation data of intercontact time distribution with the ONE simulator and then use the exponential distribution to fit the simulation data. The results are shown in Figs. 5 and 6 for RWP and MAP, respectively. From the results, we can observe that the exponential distribution fits the simulation data well, and the change of transmission range R generally does not affect the fitting quality of the results. To quantitatively investigate the fitting performance, we show the adjusted R-square, which is defined as the percentage of variation of the simulation data and fitting results, in Table I. From the table, we can observe that there is no fixed relationship between the adjusted R-square and the transmission range. However, with regard to different models, the adjusted R-square of RWP is always larger than that of MAP. The average adjusted R-square of RWP is above 99%, whereas it is 94% for the MAP model. Combined with results

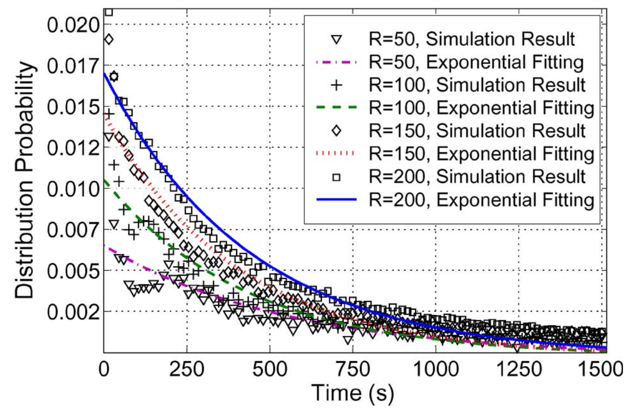

Fig. 6. Results of using exponential distribution to fit the simulation data of intercontact time obtained in the MAP model with different transmission ranges R.

TABLE I
INTERCONTACT TIME ADJUSTED R-SQUARE IN DIFFERENT MODELS WITH DIFFERENT TRANSMISSION RANGE R

Models	$R = 50$	$R = 100$	$R = 150$	$R = 200$
RWP	99.44%	99.73%	99.56%	99.31%
MAP	91.33%	93.05%	96.11%	96.57%

of the system performance, we come to the conclusion that the deviation of simulated performance from theoretical analysis is positively correlated with the deviation of the intercontact time distribution from the Poisson assumption. This further demonstrates the correctness of the theoretical results of this paper.

V. MULTICAST PERFORMANCE UNDER SELFISH BEHAVIORS

In this section, we quantify the performance of message transmission delay and transmission cost influenced by the individual and social selfishness. The parameters in our evaluation include the contact rates λ_i and λ_o, the number of relay nodes N and M, the number of destination nodes L, and the forwarding probability caused by selfishness p_{nf}, p_{nc}, p_i, and p_o. To set the parameters of contact rates, we use the Cambridge trace data set [34], which is mainly gathered by two groups of students of undergraduate years 2 and 3 from the University of Cambridge, Cambridge, U.K. From the traces, we first get the individual contact rate of each pair of nodes using the method in [31] by average statistics and then obtain the average contact rate of users in the same community $\lambda_i = 0.101$ (contacts/h) and the rate across community $\lambda_o = 0.051$ (contacts/h). The default values for the other parameters are as follows: $M + N = 50$, $L = 5, p_{nf} = 0, p_{nc} = 0, p_o = 1$, and $p_i = 1$. When we choose some of the preceding parameters and change their values, the other parameters remain their default values. To quantify the influence of selfishness on the performance, we define metrics of individual selfishness factor and social selfishness factor, which are denoted by f_i and f_s, respectively, as follows:

$$f_i \propto (p_{nf},\ p_{nc}),\ f_s \propto (1 - p_o,\ 1 - p_i). \tag{4}$$

In the analysis, we first study the influence of different selfishness behaviors on the system performance of message

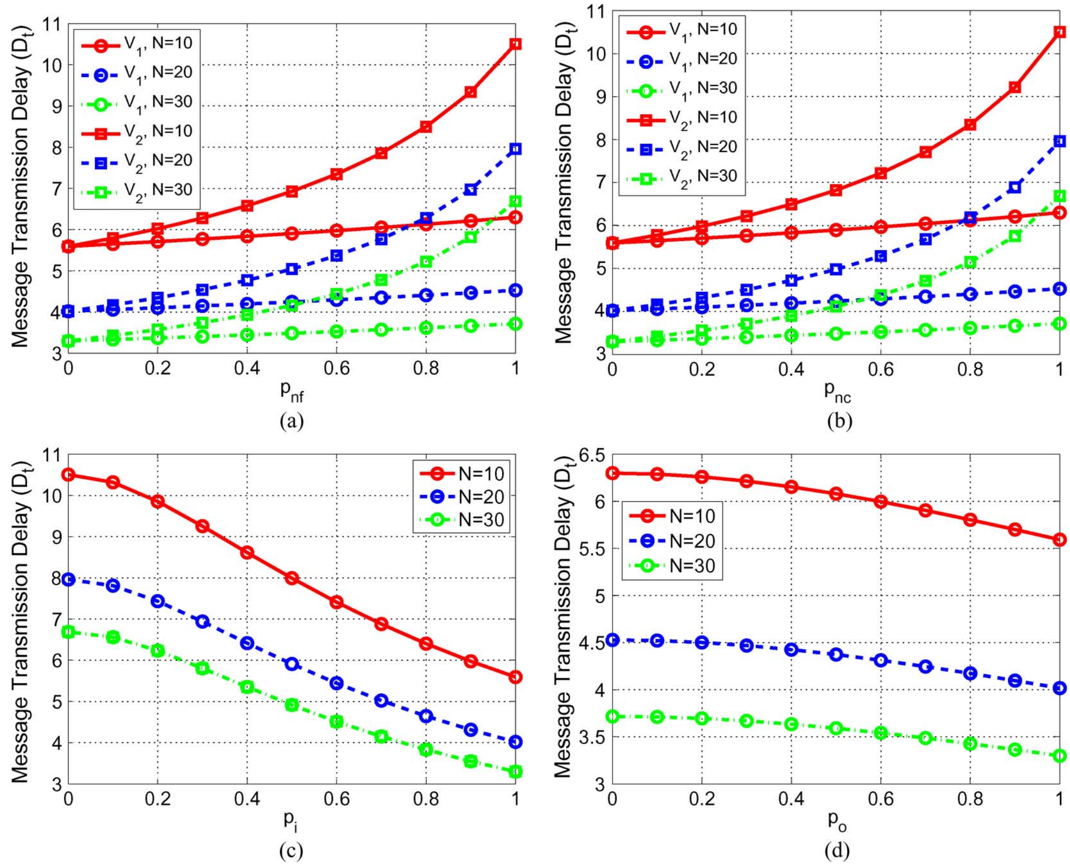

Fig. 7. Average message transmission delay of two-hop relaying multicast versus probability. (a) p_{nf}. (b) p_{nc}. (c) p_i. (d) p_o.

transmission delay and cost. Then, we compare the impact of selfishness on different relaying schemes to analyze the difference by different selfishness settings. Finally, we investigate the influence of the number of destinations on the performance of DTN multicast with selfish nodes.

A. Influence of Different Types of Selfishness

In the analysis of the different types of selfishness, we set $M = N$ and vary p_{nf}, p_{nc}, p_i, and p_o. When we investigate the individual selfishness, we study the cases that the source and destination nodes are in V_1 or are in V_2, whereas when we investigate the social selfishness, we only study the case in which the source and destination nodes are in V_1 since there is no difference if they are in V_2.

The message transmission delay of two-hop relaying with different selfish behaviors is shown in Fig. 7. In terms of individual selfishness, we observe that as p_{nf} and p_{nc} increase, which indicates the increase of the individual selfishness factor f_i, the message transmission delay increases. While in terms of social selfishness, the message transmission delay decreases with the increase of p_i and p_o, which means the decrease of the social selfishness factor f_s. Therefore, we can conclude that both socially and individually selfish behaviors deteriorate the system performance of the message transmission delay. When N increases but the selfishness-related parameters are kept the same, there are more nodes to relay the message. Although these nodes may transmit the message in a selfish way, more message transmission opportunities are created. Therefore, the message transmission delay decreases with the increase of N. Regarding individual selfishness, the impacts of p_{nf} and p_{nc} on delay are the same. The reason is that the behaviors of not forwarding and not copying messages have the same influence on the message transmission delay. Comparing the scenario where the source and destinations belong to V_1 with that where they belong to V_2, we can obtain that the individual selfishness influences the performance more significantly when the source and destinations are in community V_2. The reason is that the relay nodes in V_2 are individually selfish, which restricts the message forwarding and receiving. For the social selfishness, both p_o and p_i increase the message transmission delay, but they have different degrees of influence. For example, when $N = 20$, the delay is only reduced by 11% when p_o changes from 0 to 1. While when p_i varies from 0 to 1, the delay is reduced by about 50%. The reason is that the increase of p_i influences the nodes belonging to the same community to transmit messages more efficiently, whereas the cross-community transmission probability keeps the same. Therefore, p_i decreases the nodes' transmission probability among nodes in the same community, whereas p_o decreases the transmission probability of nodes belonging to different communities. Since the intercommunity contact rate is always larger than that of the intracommunity rate, the same reduction in p_i will influence the message transmission delay more than that in p_o. This is the reason why p_i influences the message transmission delay more than p_o.

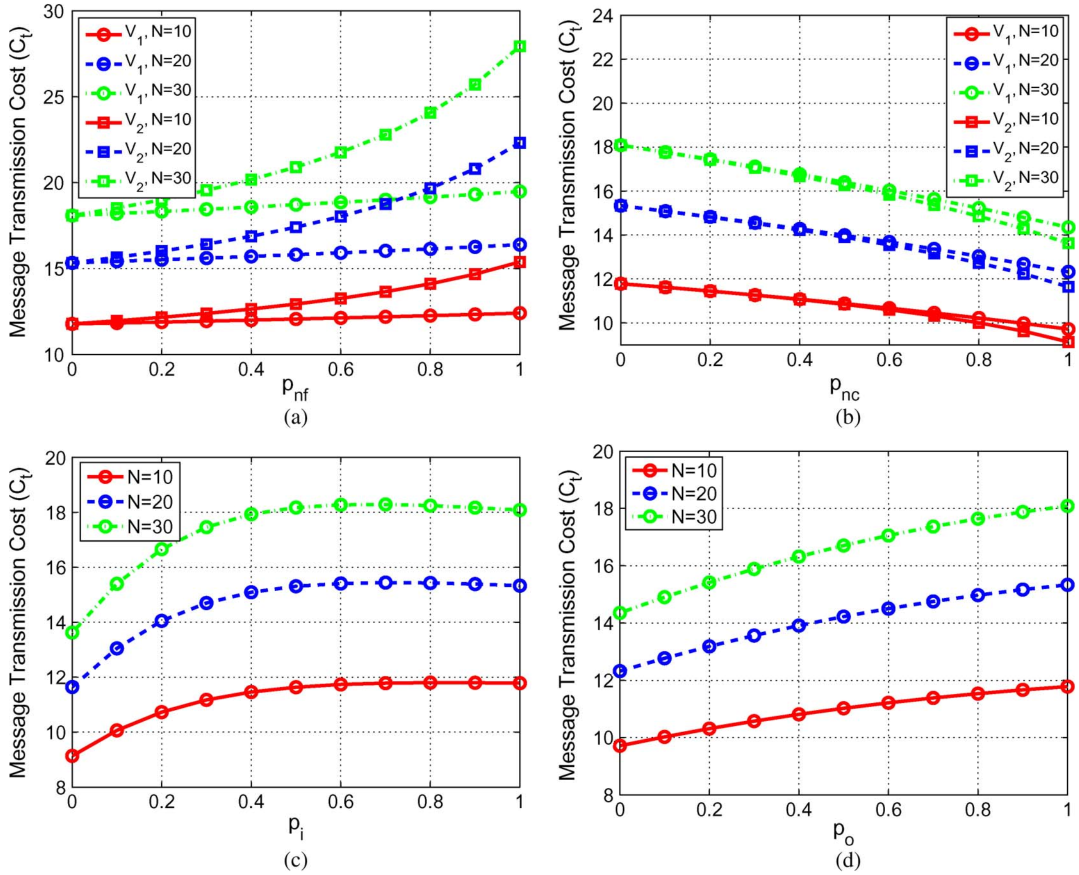

Fig. 8. Average message transmission cost of two-hop relaying multicast versus probability. (a) p_{nf}. (b) p_{nc}. (c) p_i. (d) p_o.

Fig. 8 shows the message transmission cost of two-hop relaying multicast. Different from the message transmission delay, we observe that the same selfishness factor may have an opposite influence on the cost. Specifically, when the individual selfishness factor f_i becomes larger, the cost will increase if the enhancement of f_i is caused by p_{nf}; on the other hand, the cost will decrease if the enhancement of f_i is caused by p_{nc}. The reason is that the larger the p_{nc}, which means fewer nodes are willing to copy the message, the fewer the nodes involved in the message transmission. Therefore, the message transmission times are reduced. However, the increase of p_{nf} will make it more likely that less nodes with the message are willing to forward it to others, particularly when they meet the destination nodes. This means that transmitting the message to such a node contributes less to the message delivery; consequently, it increases the transmission cost. When the source and destinations are in community V_2, the cost is larger since the delivery cost is influenced more by the relay nodes in the same community with the source and destinations, and the relay nodes in V_2 are individually selfish. From Fig. 8(c) and (d), we can obtain the influence of different socially selfish behaviors. We observe that the message transmission cost increases with the increase of p_o and p_i because the increase of p_i and p_o, which results in more message transmission, will lead to larger transmission cost.

Fig. 9 shows the results of the message transmission delay of epidemic relaying multicast. Similar to two-hop relaying, we observe that the message transmission delay increases with the decrease of the number of nodes N and decreases with the increase of the selfishness factors f_i and f_s. Therefore, we obtain the same conclusion that both socially and individually selfish behaviors deteriorate the system performance of the message transmission delay in epidemic relaying multicast. Compared with two-hop relaying, although epidemic relaying has the same variation trends in different selfishness related parameter settings, the value of the transmission delay is much smaller. For example, when we set $N = 20$, place the source and destinations in community V_1, and change p_{nf} from 0 to 1, the delay of two-hop relaying varies from 4.0 to 4.5 h, whereas that of epidemic relaying varies from 2.0 to 2.7 h, which is about 50% of two-hop relaying. The reason is that the message is forwarded in a flooding way to reduce the transmission delay in epidemic relaying. While in two-hop relaying, the message can only be forwarded by at most two hops. Therefore, although the multicast source can relay the message in an epidemic way, the message will suffer a longer transmission delay.

Fig. 10 shows the message transmission cost under epidemic relaying. The results of cost are very different from two-hop relaying. From Fig. 10(a), we can observe that the delivery cost increases with the increase of p_{nf}. Fig. 10(b) shows the influence of p_{nc} on the message transmission cost. We observe that the larger the p_{nc}, the smaller the transmission cost. Particularly when p_{nc} changes from 0.6 to 1, the cost decreasing rate is very large. This is because when p_{nc} is near 1, fewer and fewer nodes are involved in the message transmission, which saves a lot in transmission costs. At the same time, the message transmission delay increases very fast, which is shown in Fig. 9(b). In terms

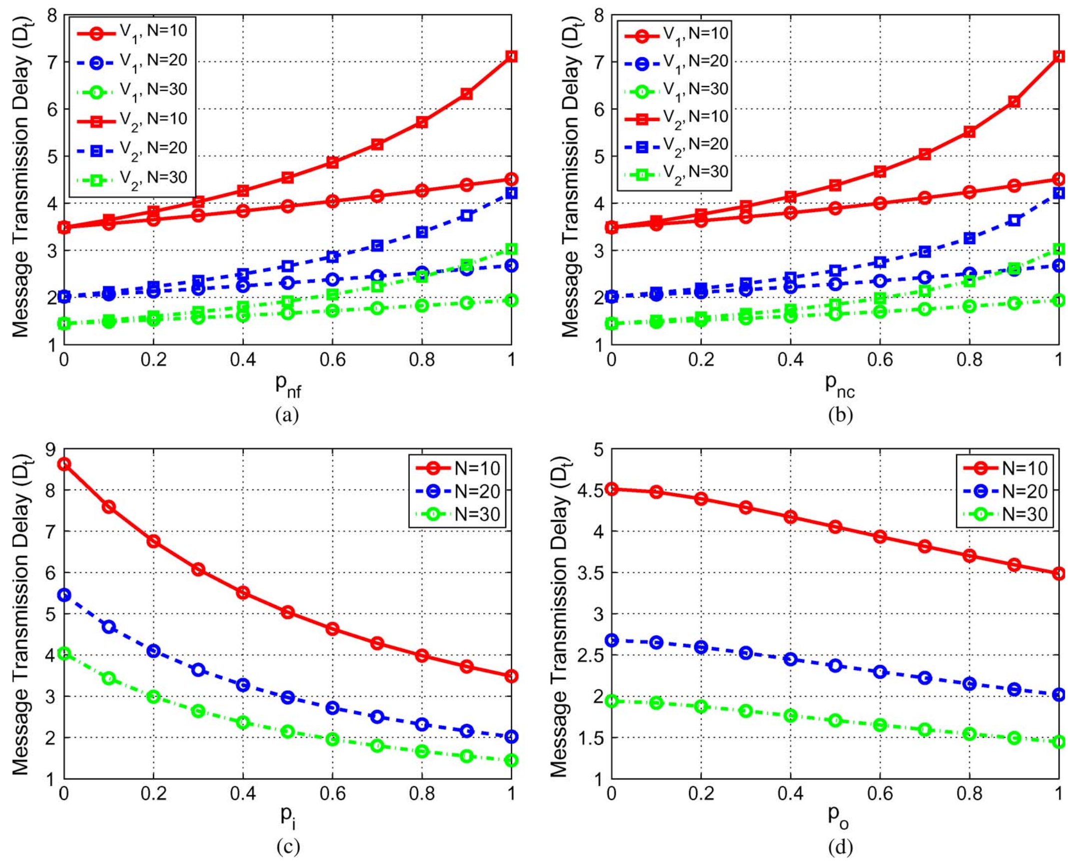

Fig. 9. Average message transmission delay of epidemic relaying multicast versus probability. (a) p_{nf}. (b) p_{nc}. (c) p_i. (d) p_o.

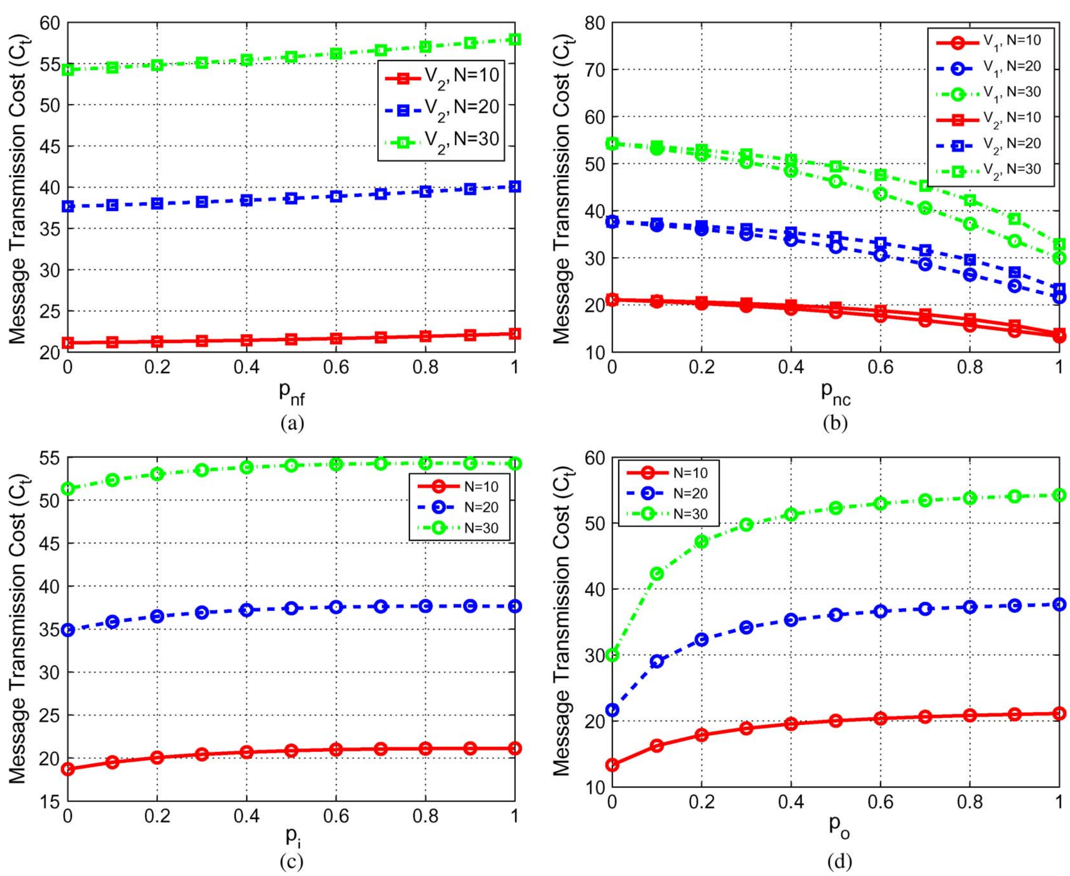

Fig. 10. Average message transmission cost of epidemic relaying multicast versus probability. (a) p_{nf}. (b) p_{nc}. (c) p_i. (d) p_o.

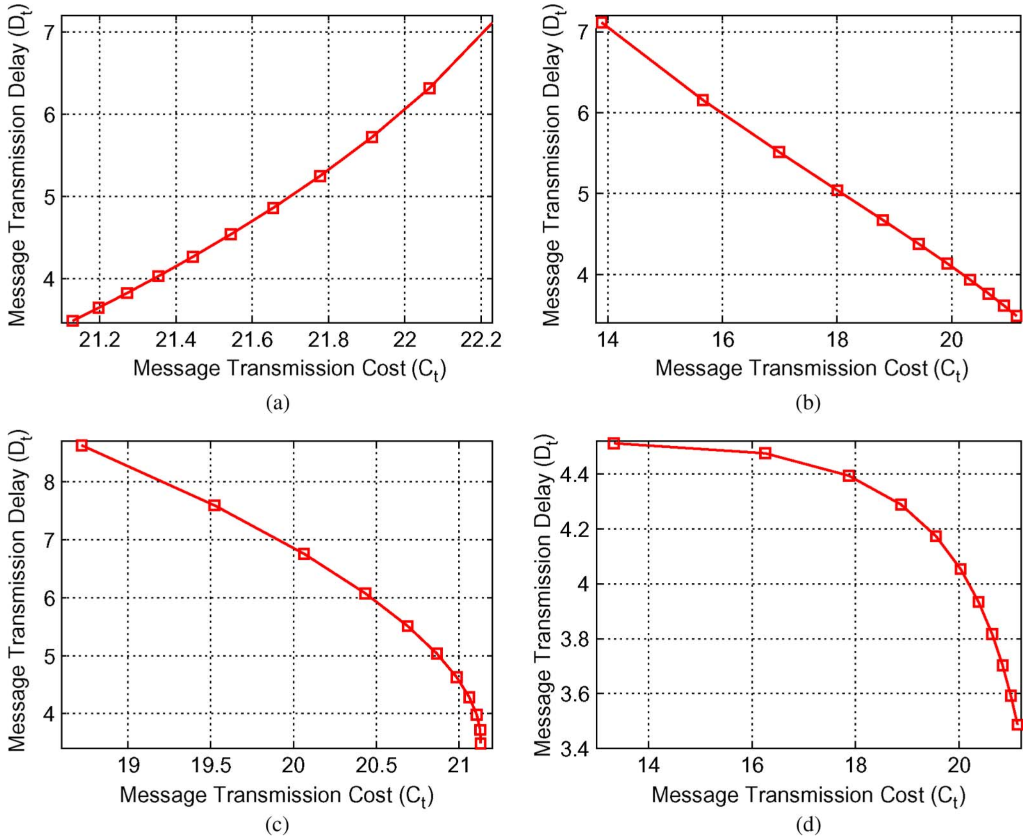

Fig. 11. Relationship between message transmission delay and cost when changing different selfishness factors between 0 and 1. (a) Varying p_{nf}. (b) Varying p_{nc}. (c) Varying p_i. (d) Varying p_o.

of social selfishness, it reduces the message transmission cost, whereas the effects of p_i and p_o are similar, as shown in Fig. 10(c) and (d). However, the impact of p_o on cost is greater than that of p_i.

From these studies, we find that different selfish behaviors have different influences on the performance metrics. Comparing the results of different relaying schemes, we find that the influences of selfishness behaviors on two-hop and epidemic relaying are the same. For different selfishness behaviors, we observe that the selfishness behavior of not forwarding message increases the message transmission delay and cost. In terms of the selfishness behavior of not copying the message, it increases the message transmission delay but reduces the transmission cost. The social selfishness related p_i and p_o increases the delay but reduces the cost. To better justify the different influences between transmission delay and cost, we study the impact of message transmission cost in the transmission delay. We choose epidemic relaying as a case study since the two-hop case is the same and plot the message transmission delay versus transmission cost by varying the selfish factors p_{nf}, p_{nc}, p_i, and p_o between 0 and 1. The results are shown in Fig. 11. When changing p_{nf}, the message delivery delay increases with the cost. That means when more nodes are selfish in not coping messages, the system performance of both delay and cost are increased. However, in the other selfish behavior case, the message transmission delay is increased but with the gain of less transmission cost. Thus, we come to the conclusion that the selfishness of not copying messages and social selfishness are not very bad since, although they may increase the message transmission delay, there is a reduction in the message transmission cost, whereas not forwarding messages is the adverse selfish behavior, which increases the delay, but there is no gain in transmission cost saving.

B. Two-Hop Versus Epidemic Relaying

Now, we focus on the different relaying schemes to investigate the impact of selfishness. From the preceding results, we observe that all the selfishness behaviors increase the message transmission delay, but here we want to know whether they have the same degree of influence on different relaying schemes. At the same time, we try to quantify the tradeoff between the performance degradation of transmission delay and the reduction of transmission cost. In this section, we assume that the source and destinations are in community V_2 since this case is better for investigating the influence of individual selfishness.

Fig. 12(a) shows the message transmission delay of two-hop and epidemic relaying with different settings for the individual selfishness. We observe that the message transmission delay increases as the number of individually selfish nodes increases. Since $M + N = 50$, the increase of N means the decrease of M. Thus, more individually selfish nodes increase the delay. Comparing different relaying schemes with the same selfishness parameters, we observe that the delay of epidemic relaying is always smaller than that of two-hop relaying. To determine whether the deterioration of the multicast performance is

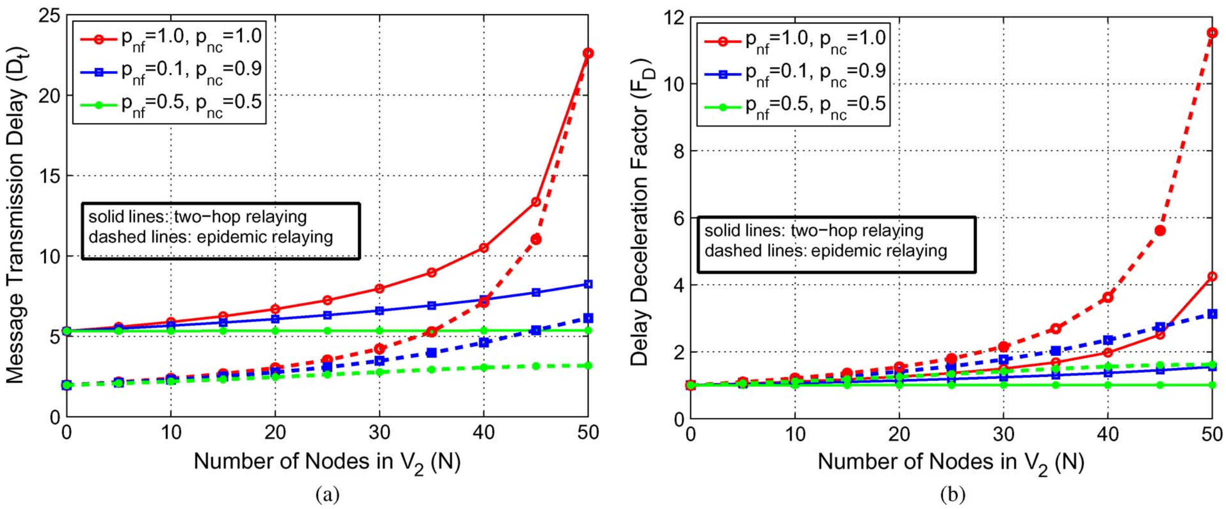

Fig. 12. (a) Message transmission delay versus N. (b) Delay deceleration factor versus N.

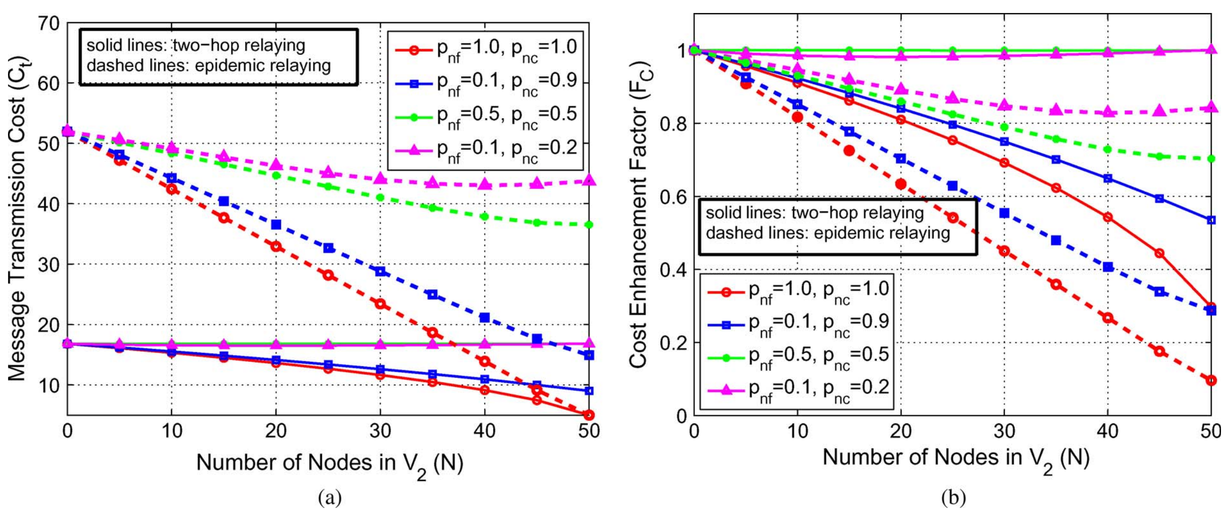

Fig. 13. (a) Message transmission cost versus N. (b) Cost enhancement factor versus N.

caused by the individual selfishness, we define a metric of delay deceleration factor, which is denoted by $F_D(N)$, as the ratio of the message transmission delay with N nodes in community V_2 versus that achieved by the scheme with the same number of nodes and none of them is individually selfish, as follows:

$$F_D(N) = \frac{D_t(N)}{D_t(0)}. \tag{5}$$

Fig. 12(b) shows the results of the delay deceleration factor, where the solid lines are for two-hop relaying, and the dashed lines are for epidemic relaying. From the results, we see that both two-hop and epidemic relaying appear quite resilient to individually selfish behaviors. For example, even when the number of selfish nodes is more than half of the total nodes and $N = 30$, the F_D's of both two-hop and epidemic relaying are very small. However, the relative performance degradation for epidemic relaying is much larger than two-hop relaying, particularly when N is larger than 30.

Fig. 13(a) shows the message transmission cost under two-hop and epidemic relaying. We observe that the cost of two-hop relaying is always smaller than epidemic relaying when the selfishness related parameters are the same. Similar to transmission delay, we define a metric of cost enhancement factor, which is denoted by $F_C(N)$, as follows:

$$F_C(N) = \frac{C_t(N)}{C_t(0)}. \tag{6}$$

Fig. 13(b) plots the result of F_C. We observe that the cost enhancement factor is less resilient to the selfishness behavior. For example, when 30 nodes become completely selfish ($p_{nc} = 1$ and $p_{nf} = 1$), the delivery cost becomes only 45% and 69% of that under the case where no node is selfish for the epidemic and two-hop relaying, respectively. When the nodes in community V_2 exhibit a completely selfish behavior, the relative performance enhancement for epidemic relaying is also much larger than two-hop relaying. Therefore, combining the results of Figs. 12 and 13, we come to the conclusion that two-hop relaying is more resilient to selfish behaviors than epidemic relaying. That is to say, the node selfishness has a higher degree of influence on the performance of epidemic relaying than that of two-hop relaying.

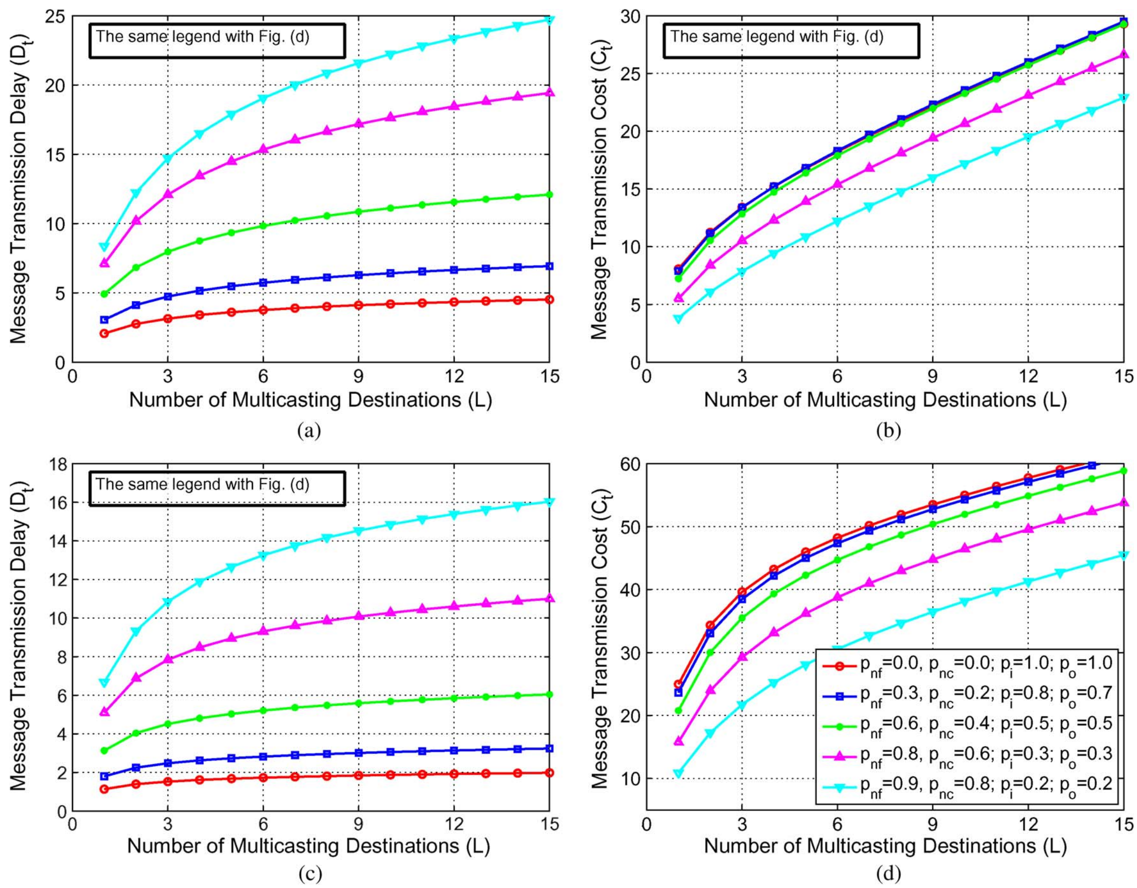

Fig. 14. (a) Message transmission delay of two-hop relaying versus L. (b) Message transmission cost of two-hop relaying versus L. (c) Message transmission delay of epidemic relaying versus L. (d) Message transmission cost of epidemic relaying versus L.

C. Influence of the Number of Multicast Users

Now, we investigate the influence of the number of multicast destination nodes on the system performance of the message transmission delay and cost. We vary the number of destinations L from 1 to 15 under different values of selfishness-related parameters and plot the results of both two-hop and epidemic relaying in Fig. 14. From these results, we observe that both the message transmission delay and the cost increase as L increases. The reason is that the more destination nodes are, the longer the time needed to deliver the message to all of them. Comparing the curves of different selfishness settings, we observe that the larger the individual and social selfishness factors, the larger the delay and cost variation influenced by the increase of L. That is to say, in the multicast with selfish nodes, the system performance will be more dependent on the number of destinations.

VI. Conclusion

In this paper, we have investigated the performance of multicast in DTNs under the influence of selfish behaviors. Our analysis shows that in the studied model, different selfish behaviors have different impacts on multicast performance metrics under different relaying schemes. In terms of different selfish behaviors, we demonstrate that in our studied case, the individual selfishness of not forwarding messages increases the message transmission delay and cost, which is detrimental to the DTN multicast, whereas the individual selfishness of not copying messages and the social selfishness increase the message transmission delay but reduce the transmission cost. Particularly in multicast applications without a restricted delay requirement, they can be used to reduce the system cost. In terms of different relaying schemes in the multicast, we show that the selfish behaviors affect epidemic relaying more than two-hop relaying. Furthermore, we observe that the increase in the number of multicast destinations increases the message transmission delay and cost. Although these conclusions are obtained in our studied models that include two communities and two different kinds of selfishness, the outcome of the studied case may be suggestive of the general behaviors since our simulation results validate the accuracy of our proposed model well. In our future work, we will focus on extending our results and conclusions to the general DTN case by using more general model and simulation settings.

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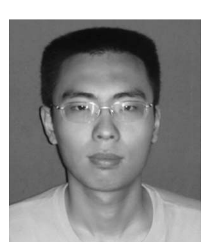

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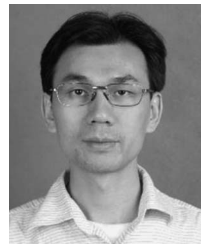

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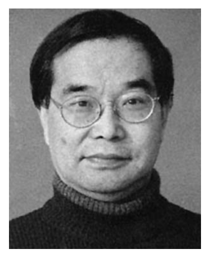

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