# An Efficient Message Dissemination Scheme for Minimizing Delivery Delay in DTNs

En Wang[1] *Member, CCF*, Wei-Shih Yang[2], Yong-Jian Yang[1,*] *Member, CCF*, Jie Wu[3] *Fellow, IEEE*, and Wen-Bin Liu[1]

[1] *Department of Computer Science and Technology, Jilin University, Changchun 130012, China*
[2] *Department of Mathematics, Temple University, Philadelphia, PA 19122, USA*
[3] *Department of Computer and Information Science, Temple University, Philadelphia, PA 19122, USA*

E-mail: wangen0310@126.com; yang@temple.edu; yyj@jlu.edu.cn; jiewu@temple.edu; nike_lwb@126.com

**Abstract** Delay tolerant networks (DTNs) are a kind of sparse and highly mobile wireless networks, where no stable connectivity guarantee can be assumed. Most DTN users have several point of interests (PoIs), and they enjoy disseminating messages to the other users of the same PoI through WiFi. In DTNs, some time-sensitive messages (disaster warnings, and search notices, etc.) need to be rapidly propagated among specific users or areas. Therefore, finding a path from the source to the destination with the shortest delay is the key problem. Taking the dissemination cost into consideration, we propose an efficient message dissemination strategy for minimizing delivery delay (MDMD) in DTNs, which first defines the user's activeness according to the transiting habit among different PoIs. Furthermore, depending on the activeness, an optimal user in each PoI is selected to constitute the path with the shortest delay. Finally, the MDMD with inactive state (on the way between PoIs) is further proposed to enhance the applicability. Simulation results show that, compared with other dissemination strategies, MDMD achieves the lowest average delay, and lower average hopcounts, on the premise that the delivery ratio is guaranteed to be 100% by the sufficient simulation time.

**Keywords** Delay Tolerant Network (DTN), point of interest (PoI), dissemination strategy, minimizing delay.

## 1 Introduction

Delay-tolerant networks (DTNs) [1, 2], are a kind of challenged networks in which end-to-end transmission latency may be arbitrarily long because the lack of stable connections. An available connected source-to-destination path may not exist. DTNs have been proposed to be used in interplanetary networks [3], disaster response networks [4], rural areas [5], wildlife tracking [6], and pocket-switched networks [7, 8]. The users in DTNs exchange their messages when they encounter each other. Successful delivery occurs only when one or more infected users encounter the destination.

Recently, the topology of mobile network is regarded as a connected graph, through which the end-to-end paths can be found. However, DTNs are occasionally connected and end-to-end paths are commonly unstable because of the mobility of nodes and instability of links. A bundle layer including the store-carry-forward paradigm [9] and the custody-transfer thought was proposed to solve the above problems. It requires the node to carry a bundle and forward it to a reliable hop until the time-to-live ($TTL$) of the bundle expires. With this in mind, choosing the suitable nodes to forward messages is the key point in DTNs.

In this paper, we consider that time-sensitive messages need to be disseminated in DTNs. For instance, a

Regular Paper
This work was supported by the National Natural Science Foundation of China under Grant No. 61772230, the National Natural Science Foundation of China Youth Fund under Grant No. 61702215, and also supported by China Postdoctoral Science Foundation under Grant No. 2017M611322.
*Corresponding Author

disaster warning message is bound to be disseminated to the users around disaster areas with the minimal delay. And a search notice must be quickly delivered to a specific area. Additionally, it is worth noticing that there are many paths from the source to the destination. Obviously, we can shorten the delivery delay through increasing message copies. However, it is not the focus of this paper. In light of the cost of dissemination, we prefer to find a path from the source to the destination with the shortest delay. Therefore, an efficient message dissemination scheme for minimizing delivery delay in DTNs is greatly needed.

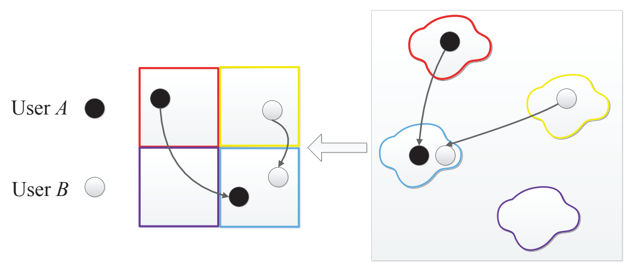



Fig. 1. Example of mapping the user's moving in physical world into the transition in grids.

In general, each DTN user has multiple interested areas (PoIs). However, each user can only be in one PoI at any given moment. As demonstrated in Fig. 1, we map the PoIs into several grids, each grid represents a PoI with the same color, and each circle represents a user, which can disseminate the message to any user in the same grid. Through the short-distance communication protocol (WiFi), the users in the same PoI can form a connection with each other, whlie they can not establish a connection when they are in different grids. If user $A$ attempts to disseminate a message to a specific PoI or user, he/she would like to choose an optimal user to help him forward the message as soon as possible. Therefore, it is not difficult to find that the transition habit among different PoIs plays an important role in terms of minimizing delay. The active user who transits frequently is bound to assist in disseminating messages, while the fallow user which stays in a PoI for a long time can not improve the dissemination performance.

In order to minimize dissemination delay, the problem changes into deciding an optimal user whose activeness is the highest. In this paper, we propose an efficient message dissemination strategy for minimizing delivery delay in DTNs, which first defines a user's activeness according to the transiting habit among different PoIs. Shorter residence time leads to more frequent transiting among PoIs, which indicates that the user has higher activeness. Similarly, longer residence time results in more sparse transiting, which means that the user has lower activeness. Subsequently, an efficient message dissemination strategy for minimizing delivery delay (MDMD) is decided on the basis of a user's activeness in order to minimize the dissemination delay. Furthermore, the MDMD with inactive state (moving between PoIs) is also proposed to enhance the applicability.

In the analysis, when the user's activeness is time-constant, the activeness has no relationship with time. In other words, whenever a specific user enters a PoI, he/she will stay there for the same expected time, and then move to another PoI. In that case, MDMD actually achieves minimal delay. However, if the activeness is time-varying, which means that the activeness is a function of time, a specific user's expected residence time in a PoI changes with time. In that case, MDMD is no longer available. In other words, each DTN user has both the instantaneous activeness, which reflects the current transiting frequency, and the long-term average activeness, which indicates the long-standing average transiting frequency. We argue that simply utilizing the instantaneous or long-term average activeness to determine the optimal user can not obtain the minimal delay performance. In this paper, in order to overcome the aforementioned problem, we choose the user who has the minimal expectation time to meet any user of another PoI to disseminate the message. Through this strategy, instantaneous activeness and long-term average activeness are both considered to make the dissemination decision. Furthermore, an efficient message dissemination strategy for minimizing delivery delay is proposed. However, MDMD without considering the user's inactive state (moving between PoIs) can be further improved. Hence, we enhance the MDMD by adding the inactive state to further enhance the applicability. Simulation results show that, compared with other dissemination strategies, the enhanced MDMD achieves the lowest average delay, and lower average hopcounts compared with the other strategies, on the premise that the delivery ratio is guaranteed to be 100%.

The main contributions of this paper are briefly summarized as follows:

- We define the user's activeness in DTNs according to the transiting habit among different PoIs, with a higher transiting frequency meaning higher activeness, and vice versa.
- According to the user's activeness, an efficient message dissemination scheme for minimizing delivery delay (MDMD) is proposed in DTNs. The situation in which the user's activeness is time-varying is also considered to further improve the proposed scheme. We further enhance the MDMD by considering the inactive state (moving between PoIs).
- We conduct extensive simulations based on the synthetic user's activeness. The results show that, compared with other dissemination strategies, MDMD achieves the lowest average delay, and lower average hopcounts compared with the other strategies.

The remainder of the paper is organized as follows. We review the related work in Section 2. The efficient message dissemination strategy for minimizing delivery delay in DTNs (MDMD) is presented in Section 3. The enhanced MDMD by considering inactive state is discussed in Section 4. In Section 5, we evaluate the performance of MDMD through extensive simulations. We conclude the paper in Section 6. Our proofs are presented in the Appendix.

## 2 Related Work

According to different concerns and perspectives, the state-of-the-art research achievements are best summarized by the following three points. The first part focuses on the forwarding metric, which is used to measure the forwarding ability of a user in DTNs. The second part pays attention to proposing buffer management strategies, which use the limited buffer space to efficiently deliver the messages. The third part concentrates on proposing the forwarding strategy, which controls the number of forwarding copies and the chance to forward the messages.

### 2.1 Forwarding Metric

Forwarding metric is used to measure the strength of a connection, and further quantify the node's forwarding ability. The forwarding metric can be destination-specific or destination-independent [10]. A destination-specific forwarding metric varies depending on the destination of a message. For example, fresher encounter search (FRESH) [11] uses the time elapsed since the last contact with the destination as a forwarding metric. However, some forwarding metrics such as the total contact rate of a node have no relationship with the different destinations, and hence, are regarded as destination-independent. In [12], authors first designed a novel forwarding metric to measure the forwarding capability. Then, they utilizd small-world properties to design the principles of relay node selection. [13] proposes two forwarding algorithms for opportunistic broadcast forwarding, which make the forwarding decision by comparing the current energy efficiency with the estimated future expectation.

In this paper, the transiting frequency is regarded as the forwarding metric, which is destination-independent and time-varying. The short-term average activeness and long-term long-term average activeness are used to reflect the nodes' transient and longstanding forwarding abilities, respectively. We argue that simply using the short-term or long-term activeness as the forwarding metric can not obtain the optimal delivery performance.

### 2.2 Buffer Management

Zhang *et al*. [9] developed a rigorous and uniform framework based on ordinary differential equations (ODEs) to discuss Epidemic routing and its relevant variations. They also investigated how the buffer space and the number of message copies can be addressed for the fast and efficient delivery. The work in [14] proposed a new message scheduling framework for both Epidemic and two-hop forwarding routings in DTNs; the scheduling and dropping decisions can be made in each contact duration in order to achieve either optimal message delivery ratio or average delay. Krifa and Barakat in [15] proposed an idealized strategy called the Global Knowledge-Based Scheduling and Drop strategy (GBSD), in which signal overhead is reduced by optimizing the storage structure and statistics-collection method. [16] proposed a Message Scheduling and Drop Strategy on Spray and Wait Routing Protocol (SDSRP), which calculates the priority of each message by evaluating the impact of both replicating and dropping a message copy on delivery ratio. [17] proposed two routing algorithms, namely local information-based routing (LIR) and local and neighbour information-based routing (LNIR) for space DTNs, according to the queueing information.

The above studies focus on the buffer management in DTNs. To a certain extent, they can improve the message delivery ratio or reduce the delivery delay in DTNs. However, the above work focus on the multi-copy situation, which is different from the problem of this paper.

### 2.3 Forwarding Strategy

There is also plenty of work that focuses on forwarding strategy in DTNs. Tatiana *et al*. [18] persuaded mobile nodes to participate in relaying messages. Indeed, the delivery of a message incurs a certain number of costs for a relay. Wang *et al*. [19] presented the retransmission timeout (RTO) timer setting for reliable file transmission over a relay-based deep-space vehicle communication infrastructure. Li *et al*. [20] proposed a novel social-based routing approach for mobile social DTNs, where a new metric social energy is introduced to quantify the ability of a node to forward packets to others. Sabbagh *et al*. [21] presented analytical modeling of the transmission performance of bundle protocol over deep-space communication channels characterized by highly asymmetric channel rate. Sakai *et al*. [22] designed an abstract of anonymous routing protocols for DTNs and augmented the existing solution with multi-copy message forwarding. [23] proposes a probabilistic routing protocol for the intermittently connected networks. [24] constructs generative route-level models that capture the variability in bus movement and the random failures to establish connections. [25] introduced a new family of routing schemes, which "spray" a few message copies into the network, and then the schemes route each copy independently towards the destination.

In this paper, we attempt to minimize the dissemination delay in DTNs. On the one hand, we attempt to find only one path from the source to the destination with the shortest delay. On the other hand, we prefer to make as few users as possible participate in the dissemination process. Therefore, in each PoI, only one optimal user is selected to disseminate messages.

## 3 Efficient Message Dissemination Strategy for Minimizing Delivery Delay in DTNs

In order to clearly describe the process of message dissemination and strategy insights, we first introduce the assumptions related to the work, briefly describing the problem to be solved. Next, a continuous time markov model is used to measure the message dissemination delay to achieve optimal user activeness through the transition habit among different PoIs. Finally, the time-constant and time-varying activeness are both considered to minimize the message dissemination delay, and the efficient message dissemination strategy is further proposed in DTNs.

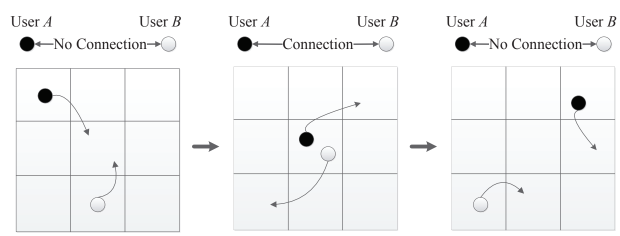



Fig. 2. Description of the message dissemination problem.

### 3.1 Assumptions

We consider the following DTN environment: there are $l$ users, who move around $n$ different PoIs. At any specific time, a user can be active in only one PoI. Moreover, a user's residence time obviously has an expected value. Besides, all the users have a short residence time and move towards to another PoI, for the reason that they may have some crucial work to do. Therefore, the users can hardly be in a PoI for too long time. Therefore we assume that the residence time at each PoI satisfies an exponential distribution. The term, "residence time", simply refers to the time a user stays in a

PoI either receiving or disseminating messages. Different users' residence time satisfies different distributions, and the specific user's residence time in different PoIs obeys the same distribution. The message is generated by a user with the lowest activeness at the initial system time, and each message has only one copy and a given $TTL$, after which the message is no longer useful. Two users in the same PoI can disseminate messages to each other. The destination user is considered to be stationary and has the highest priority, which means that any message holder attempts to disseminate the message to the destination. Neither an immunization strategy nor an acknowledgment mechanism is used to confirm the receipt of messages for the reason that there is only one copy.

### 3.2 Problem Solution

As shown in Fig. 2, user $A$ and user $B$ can establish a connection when they are in the same PoI, but the connection breaks when they transit to different PoIs. In this paper, we attempt to utilize the user of the highest activeness to assist in disseminating messages, in order to minimize the dissemination delay from the source to the destination. However, the following three questions are still urgent issues to be tackled: 1) How to define the user's activeness. 2) When the user's activeness is time-constant, what kind of dissemination strategy we should adopt. 3) What about the situation that the user's activeness is time-varying.

In order to overcome the aforementioned problem, we first define the user's activeness through the transition habit among different PoIs, which is reflected by the parameter value of exponential distribution. Then, we choose the user with the highest activeness to disseminate the message when the activeness is time-constant. However, when the activeness is time-varying, we choose the user who has the minimal expectation time to meet any user of another PoI to disseminate the message. Through this strategy, an efficient message dissemination strategy for minimizing delivery delay is proposed in DTNs. The pseudo-codes of MDMD are described in Algorithm 1 and Algorithm 2. The main notations used in this paper are illustrated in Table 1.

### 3.3 Continuous-Time Markov Model

#### *3.3.1 Definition of Activeness*

In this subsection, we utilize two specific users ($A$ and $B$) to illustrate the continuous-time markov model. First of all, we use $X_t$ to express the state (PoI being used) of user $A$ at time $t$. It is not difficult to find that $X_t \in e = \{e_1, e_2, \cdots, e_n\}$. This is due to the reason that, in the previous subsection, we assume that the time spent in each PoI takes non-negative value and obeys an exponential distribution. Therefore, we consider that $X_t$ satisfies the continuous-time markov chain.

We define $P_{ij}(t)$ as the probability that a user's state of time 0 is $i$ and the state of time $t$ is $j$, which is shown as follows: $P_{ij}(t) = P(X_t = j|X_0 = i)$. Without loss of generality, we regard $\boldsymbol{P}(t)$ as the $n \times n$ matrix composed of $P_{ij}(t)$. We can generate the transition rate matrix $\boldsymbol{P}$ of continuous-time markov chains (as shown in (1)) through the following formula: $\boldsymbol{P} = \lim\limits_{t\to 0} \frac{\boldsymbol{P}(t)-\boldsymbol{P}(0)}{t-0} = \lim\limits_{t\to 0} \frac{\boldsymbol{P}(t)-\boldsymbol{I}}{t}$, where $\boldsymbol{I}$ is the unit matrix.

$$\boldsymbol{P} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots & \vdots \\ \cdots & \cdots & \cdots & a_{nn} \end{pmatrix}. \quad (1)$$

The detailed characteristics of transition rate matrix $\boldsymbol{P}$ are listed as follows:

1) $a_{ii} < 0$ $(\forall i)$, $\sum\limits_{j=1}^{n} a_{ij} = 0$, $a_{ij} \geq 0$ $(\forall i \neq j)$.

2) The user holding the message at PoI $e_i$ waits for a random time $\tau_i$, and then transits to $e_j$ with the probability: $q_{ij} = \frac{a_{ij}}{-a_{ii}}$. Due to the reason that the residence time satisfies an exponential distribution, $\tau_i \sim \exp(-a_{ii})$, which indicates that $\tau_i$ satisfies the exponential distribution with parameter $-a_{ii}$.

3) When the user holding the message stays in state $i$, it has an equal probability of transition from the current state to any other state, which means that the following equation is satisfied: $q_{ij_1} = q_{ij_2}$ $(\forall j_1, j_2 \neq i)$.

4) The discrete states of $X_t$ are expressed as: $\overline{X_0}$, $\overline{X_1}$, $\cdots$, $\overline{X_t}$, which satisfy discrete-time markov chains.

5) The larger the $-a_{ii}$ is, the higher the user's activeness is. Similarly, the smaller the $-a_{ii}$ is, the lower the user's activeness is.

**Table** 1. Main Notations Used Throughout The Paper

| Notation | Explanation |
|---|---|
| $n$ | Number of PoIs (number of grids) |
| $e$ | Set of PoIs, $e=\{e_1, e_2, \cdots, e_n\}$ |
| $X_t$ | User's state (PoI ID) at time $t$, $X_t \in e$ |
| $P_{ij}(t)$ | Probability that user's state of time 0 is $i$, and the state of time $t$ is $j$ |
| $\tau_i$ | Residence time to stay in PoI $e_i$ |
| $\tau$ | Earliest time for user $l$ to meet someone else |
| $c_k$ | Parameter in exponential distribution of user $k$'s residence time |
| $T$ | Earliest time for two users to meet each other |
| $E_{ij}(T)$ | Earliest expected time for two users to meet, with the condition that their initial states are $i$ and $j$ |
| $\xi$ | The first transition time (from one PoI to another one) for any one of the two users |
| $l$ | Total number of users |
| $T_i$ | The first meeting time between user $i$ and user $l$ |
| $\lambda_{l,i}$ | Parameter of $T_i$'s exponential distribution, $\lambda_{l,i} = \frac{c_l+c_i}{n-1}$ |
| $T^{(l)}$ | Dissemination delay from the lowest priority user to the highest priority user for a $l$-users system |
| $r_l$ | Expectation of $T^{(l)}$ |
| $\sigma_i$ | The first meeting time between user $i$ and anyone else |
| $c_i(t)$ | Time-varying parameter of the exponential distribution at time $t$ |
| $X_i^*$ | Predicted intermeeting time for user $i$ to meet any other user |

In conclusion, each user has its corresponding transition rate matrix, where the negative diagonal $-a_{ii}$ represents its activeness. (2) is a detailed example to further illustrate the user's activeness:

$$\boldsymbol{M_A} = \begin{pmatrix} -2 & 1 & 1 \\ 1 & -2 & 1 \\ 1 & 1 & -2 \end{pmatrix}, \tag{2}$$

where $n = 3$ means that there are three PoIs in DTNs. $a_{ii} = -2$ indicates that the user's activeness is 2, and the expectation residence time satisfies: $\tau_i \sim \exp(2)$. In addition, the transition probability from state $i$ to state $j$ satisfies the following equation: $a_{ij} = 1/2$ ($\forall i \neq j$). Therefore, for this example, the user's residence time in each PoI satisfies the exponential distribution with parameter 2, and the user has the probability of 1/2 to transit from current PoI to anyone else.

#### 3.3.2 *Expectation Time of the First Meeting between Users A and B*

Since this research focuses on minimizing dissemination delay, the expectation meeting time between users $A$ and $B$, then plays an important role. Suppose that the state of user $A$ at time $t$ is $X_t$, and the state of user $B$ at time $t$ is $Y_t$. Simultaneously, according to the derivation in the Subsection 3.3.2, the transition rate matrixes of user $A$ and user $B$ are shown in (3) and (4), respectively. Moreover, on the basis of the character 1) of continuous-time markov chain's transition rate matrix, $a$ and $b$ are calculated through following two equations: $a = \frac{c_1}{n-1}$, $b = \frac{c_2}{n-1}$. In addition, according to the character 3) of the transition rate matrix, user $A$ and user $B$ have the same probability $\frac{1}{n-1}$ of transiting from current PoI to another one. Their expectation residence time also satisfies the exponential distributions with parameters $c_1$ and $c_2$, respectively.

$$\boldsymbol{M_A} = \begin{pmatrix} -c_1 & a & a & a \\ \vdots & \vdots & \vdots & \vdots \\ \cdots & \cdots & \cdots & -c_1 \end{pmatrix}. \tag{3}$$

$$\boldsymbol{M_B} = \begin{pmatrix} -c_2 & b & b & b \\ \vdots & \vdots & \vdots & \vdots \\ \cdots & \cdots & \cdots & -c_2 \end{pmatrix}. \tag{4}$$

We define the earliest time for $A$ and $B$ to meet each other as $T = inf\{t \geq 0; X_t = Y_t\}$, which means the minimal nonnegative value $t$ satisfying $X_t = Y_t$. Assume that the initial states of users $A$ and $B$ are $X_t = i$ and $Y_t = j$, respectively. We define the notation of condition probability as: $E_{ij}(\bullet) = E(\bullet | X_0 = i, Y_0 = j)$, which indicates the expectation of the earliest time for users $A$ and $B$ to meet each other with the condition that $X_t = i$ and $Y_t = j$. It is not difficult to find that our purpose changes into finding the value of $E_{ij}(T)$.

As previously mentioned, the state of user $A$ is $X_t$, and the state of user $B$ is $Y_t$, we define $\xi^X$ as user $A$'s first transiting time from the current PoI to another one, and $\xi^Y$ is user $B$'s first transiting time. We also define $\xi = \min\{\xi^X, \xi^Y\}$ as the minimal transiting time between user $A$ and user $B$. According to the previous assumptions, Theorem 1 is achieved as follows:

**Theorem 1.** $\xi^X \sim \exp(c_1)$, $\xi^Y \sim \exp(c_2)$, *and then* $\xi \sim \exp(c_1 + c_2)$.

The proof of Theorem 1 is shown in Appendix $A1$, where we can achieve $E_{ij}(\xi) = \frac{1}{c_1+c_2}$. The insight meaning of Theorem 1 is shown as follows. The expectation of user $A$'s first transiting time is $\frac{1}{c_1}$, and the expectation of user $B$'s first transiting time is $\frac{1}{c_2}$. However, the minimal expectation of transiting time for either $A$ or $B$ is $\frac{1}{c_1+c_2}$, which is lower than $\frac{1}{c_1}$ and $\frac{1}{c_2}$. This is natural and reasonable. Based on Theorem 1, Theorem 2 is further obtained.

**Theorem 2.** $\xi^X \sim \exp(c_1)$, $\xi^Y \sim \exp(c_2)$, *the earliest time for users $A$ and $B$ to meet each other* $(T = inf\{t \geq 0; X_t = Y_t\})$ *satisfies*: $T \sim \exp(\frac{c_1+c_2}{n-1})$.

The proof of Theorem 2 is shown in Appendix $A2$. Theorem 2 shows the distribution of the expectation time for the first meeting of $A$ and $B$, which clarifies the following: due to the reason that $T \sim \exp(\frac{c_1+c_2}{n-1})$, $E_{ij}(T) = \frac{n-1}{c_1+c_2}$. There are three variables: $c_1$, $c_2$, and $n$. It is worth noticing that larger $c_1$ or $c_2$ leads to shorter first meeting time of $A$ and $B$. In other words, higher user activeness leads to earlier meeting time. In addition, larger $n$ results in longer first meeting time. That is to say, more PoIs result in longer meeting time, which also makes sense.

This subsection defines the parameter of the exponential distribution obeyed by a user's residence time in each PoI as a user's activeness. According to the user's activeness, we achieve the expectation time for the first meeting between two users, which plays a major role in making a message dissemination strategy, aiming to minimize delivery delay.

### 3.4 Time-Constant Activeness

We consider the delay tolerant network with $l$ users, whose activeness (the parameter of exponential distribution regarding residence time in each PoI) is different and time-constant [26]. In other words, their priorities can be sorted from low to high. Assume that the activeness of $l$ users in the network is $c_1$, $c_2$, $\cdots$, $c_l$, while their priorities satisfy $c_1 > c_2 > \cdots > c_l$. Without loss of generality, the user with the lowest priority $c_l$ is assigned as the message holder, meanwhile, the destination user is considered to have the highest priority. There is only one message holder in DTN at the same moment. The purpose is to make a dissemination decision for the message holder in order to minimize delay.

$T_1$, $T_2$, $T_3$, $\cdots$, $T_{l-1}$ are used to represent the first meeting time between user $l$ and user 1, 2, 3, $\cdots$, $l-1$, respectively. According to Theorem 2, $T_i \sim \exp(\frac{c_l+c_i}{n-1})$ is achieved. The following symbolic representations are made in order to simplify the expression regarding the parameter of exponential distribution: $\lambda_{l,1} = \frac{c_l+c_1}{n-1}$, $\cdots$, $\lambda_{l,l-1} = \frac{c_l+c_{l-1}}{n-1}$. The following two theorems are listed in order to further propose a message dissemination strategy for minimizing delay, when the user's activeness is time-constant.

**Theorem 3.** $P(T_j < T_i, \forall i \neq j) = \frac{\lambda_{l,j}}{\lambda_{l,1}+\lambda_{l,2}\cdots+\lambda_{l,l-1}}$.

*Proof.* consider the delay tolerant network with $l$ users, the activeness of user $i$ is $c_i$, and $\lambda_{l,i} = \frac{c_l+c_i}{n-1}$. The detailed proof process of Theorem 3 is shown in (5), where $\chi$ means the constraint of calculation process.

$$
\begin{aligned}
&P(T_j < T_i, \forall i \neq j) \\
&= \int_0^\infty \cdots \int_0^\infty \chi_{t_j < t_i, \forall i \neq j} \prod_{i=1}^{l-1} (\lambda_{l,i} e^{-\lambda_{l,i} t_i}) \mathrm{d}t_1 \cdots \mathrm{d}t_{l-1} \\
&= \int_0^\infty \lambda_{l,j} \prod_{i=1}^{l-1} e^{-\lambda_{l,i} t_j} \mathrm{d}t_j \\
&= \frac{\lambda_{l,j}}{\lambda_{l,1} + \lambda_{l,2} \cdots + \lambda_{l,l-1}}.
\end{aligned} \tag{5}
$$

□

**Theorem 4.** $E[T_j \chi_{T_j=\tau}] = \frac{\lambda_{l,j}}{(\lambda_{l,1}+\lambda_{l,2}\cdots+\lambda_{l,l-1})^2}$.

*Proof.* the proof process of Theorem 4 is similar to the one of Theorem 3. Consider the DTN with $l$ users as before, the proof process of Theorem 4 is shown in (6).

$$E[T_j\chi_{T_j=\tau}]= \int_0^\infty \lambda_{l,j}t_j \prod_{i=1}^{l-1} e^{-\lambda_{l,i}t_j}\mathrm{d}t_j$$
$$= \int_0^\infty \frac{\lambda_{l,j}}{\sum_{i=1}^{l-1}\lambda_{l,j}} \sum_{i=1}^{l-1}\lambda_{l,j}t_j e^{\sum_{i=1}^{l-1}\lambda_{l,j}t_j}\mathrm{d}t_1$$
$$= \frac{\lambda_{l,j}}{(\lambda_{l,1}+\lambda_{l,2}\cdots+\lambda_{l,l-1})^2}. \quad (6)$$

The purpose is to formulate a dissemination strategy for the message holder in order to minimize dissemination delay. As shown in Table 1, the dissemination delay from the lowest priority user to the highest priority user for an $l$-user system is defined as $T^{(l)}$. Similarly, the dissemination delay for a $j$-user system is $T^{(j)}$. The problem changes into calculating the expectation of $T^{(l)}$, which is shown in (7), where the calculation of $E(T^{(l)})$ is divided into following two parts: $E[T_j]$ and $E(T^{(j)})$.

$$E(T^{(l)})= \sum_{j=1}^{l-1}\{E[T_j\chi_{T_j=\tau}]+P(T_j<T_i,\forall i\neq j)E(T^{(j)})\}. \quad (7)$$

In order to simplify symbolic representation, we define that $E(T^{(l)})=r_l$, $E(T^{(j)})=r_j$. And then (8) is achieved, Theorem 4 is further proposed.

$$r_l = \sum_{j=1}^{l-1}[\frac{\lambda_{l,j}}{(\lambda_{l,1}+\lambda_{l,2}+\cdots+\lambda_{l,l-1})^2} + \frac{\lambda_{l,j}}{\lambda_{l,1}+\lambda_{l,2}+\cdots+\lambda_{l,l-1}}r_j]$$
$$= \frac{1}{\lambda_{l,1}+\lambda_{l,2}+\cdots+\lambda_{l,l-1}} + \frac{\sum_{j=1}^{l-1}\lambda_{l,j}r_j}{\lambda_{l,1}+\lambda_{l,2}+\cdots+\lambda_{l,l-1}}. \quad (8)$$

□

**Theorem 5.** *With the condition that* $\lambda_{l,1}>\lambda_{l,2}>\cdots>\lambda_{l,l-1}$, *if we exchange any pair of priorities* $\lambda_{l,i}$ *and* $\lambda_{l,j}$, *then* $r_l$ *will get bigger.*

The proof of Theorem 5 is shown in Appendix $A3$, which illustrates that, if we exchange any pair of initial priorities of $\lambda$, the expectation of dissemination delay will be longer compared with the original schedule. In other words, the best strategy for minimizing dissemination delay is to disseminate the message according to the priority: $\lambda_{l,1}>\lambda_{l,2}>\cdots>\lambda_{l,l-1}$. Therefore, when the user's activeness is time-constant, the optimal dissemination strategy is achieved, which disseminates the message to the user of the highest activeness in the current PoI, in order to minimize dissemination delay.

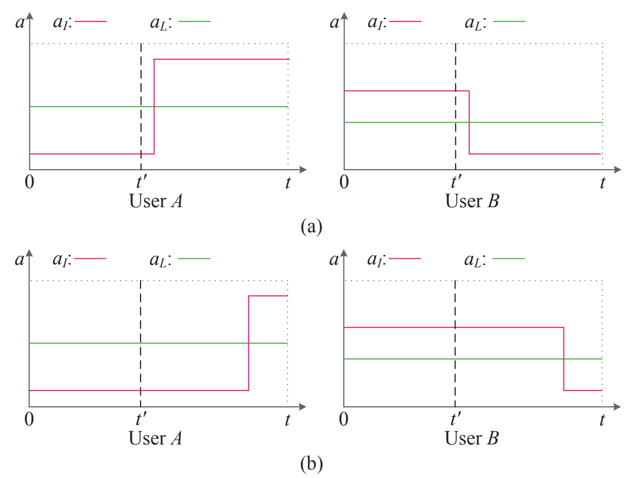



Fig. 3. The problem descriptions of the two cases in which the user for disseminating the message is chosen according to instantaneous activeness and long-term average activeness, respectively. (a) Case 1: depend on instantaneous activeness. (b) Case 2: depend on long-term average activeness.

### 3.5 Time-Varying Activeness

This subsection considers the situation in which the user's activeness is time-varying, so that the user's current activeness can not represent the actual activeness in a period of time. When the user's activeness is time-varying, each user has both instantaneous activeness and long-term average activeness. We argue that simply utilizing the instantaneous or long-term average activeness to make the dissemination decision (as shown in Fig. 3) can not obtain the minimal delay performance. As shown in Fig. 3, $a_I$ is instantaneous activeness, $a_L$ is long-term average activeness, $tc$ is the meeting time in the same PoI between users $A$ and $B$. In case 1, according to the instantaneous activeness, user $A$ makes the decision to disseminate the message to user $B$. In case 2, according to the long-term average activeness, user $A$ makes the decision to keep the message from disseminating to user $B$. However, the above decisions are both incorrect in terms of minimizing delay. Therefore, aiming to minimize the dissemination delay, the message holder chooses the user with the minimal expectation time to meet any user of another

PoI to disseminate the message.

We use $\sigma_i$ to express the first meeting time between user $i$ and anyone else. The purpose is to find the user with the minimal expectation time to meet any user of another PoI. Therefore, we need to calculate $E(\sigma_i)$ for all the users within the current PoI, and choose the user with the smallest $E(\sigma_i)$ to disseminate the message. We also define that, $T_{ij}$ is the first meeting time between users $i$ and $j$; it is proved that $T_{ij}\sim\exp(\frac{c_i+c_j}{n-1})$, and we also conclude that $\lambda_{ij}=\frac{c_i+c_j}{n-1}$. According to Theorem 4, it is not difficult to determine that $E[T_{ij}\chi_{T_{ij}=\sigma_i}]=\frac{\lambda_{ij}}{(\sum\limits_{k\neq i}\lambda_{ik})^2}$. Therefore, the final expression of $E(\sigma_i)$ is obtained through (9).

$$E(\sigma_i)=\sum_{k\neq i}[T_{ik}\chi_{T_{ik}=\sigma_i}]=\sum_{k\neq i}\frac{\lambda_{ik}}{(\sum\limits_{k\neq i}\lambda_{ik})^2}$$
$$=\frac{1}{\sum\limits_{k\neq i}\frac{c_i+c_k}{n-1}}=\frac{n-1}{(l-2)c_i+\sum\limits_{k}c_k}. \tag{9}$$

Due to the reason that a user's activeness is time-varying, $c_1$, $c_2$, $\cdots$, $c_l$ can be expressed as $c_1(t)$, $c_2(t)$, $c_3(t)$,$\cdots$, $c_l(t)$. As shown in Fig. 4, the average activeness in time period $X$ for user $i$ is defined as $\overline{c_i(X)}=\frac{1}{X}\int_{t_0}^{t_0+X}c_i(s)\mathrm{d}s$. We make the following function of $X$: $f_i(X)=E[\sigma_i(X)]=\frac{n-1}{(l-2)\overline{c_i(X)}+\sum\limits_{k}\overline{c_k(X)}}$. The purpose is to find $X_i^*$ satisfying $f_i(X_i^*)=X_i^*$ for each user $i$. Subsequently, when users $i$ and $j$ meet each other, if $X_i^*>X_j^*$ , then $i$ disseminates the message to $j$. Otherwise, $i$ does not disseminate the message.

**Theorem 6.** *If* $f_i(X)=\frac{n-1}{(l-2)\overline{c_i(X)}+\sum\limits_{k}\overline{c_k(X)}}$ *is a continuous function, then* $\exists X_i^*$ *satisfying* $f_i(X_i^*)=X_i^*$.

*Proof.* Assume $0<c\leq c_i(X)\leq d$, then $c\leq\overline{c_i(X)}\leq d$, and then $2(l-1)c\leq(l-2)\overline{c_i(X)}+\sum\limits_{k}\overline{c_k(X)}\leq 2(l-1)d$. Therefore, (10) is achieved, considering that $f_i(X)$ is a continuous function satisfying following mapping: $[\frac{n-1}{2(l-1)d},\frac{n-1}{2(l-1)c}]\rightarrow[\frac{n-1}{2(l-1)d},\frac{n-1}{2(l-1)c}]$. As shown in Fig. 5, according to the intermediate value theorem① , there must be $X\in[a,b]$, which satisfies $f(X)=X$. In conclusion, when a user's activeness is time-varying, we can make the dissemination decision through the solution $X$, in order to minimize the dissemination delay in DTNs. In other words, we choose the user who has the minimal expectation time to meet any user of another PoI to disseminate the message.

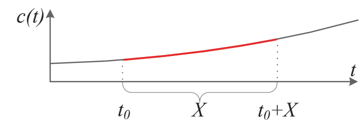



Fig. 4. Relationship between $t_0$ and $X$.

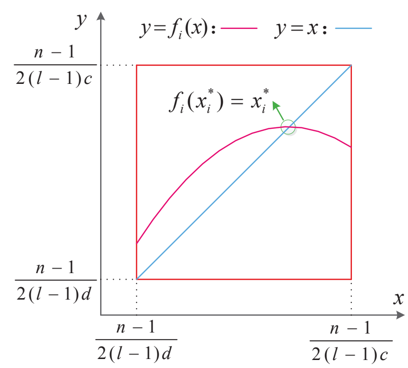



Fig. 5. Illustration of Theorem 6 through the intermediate value theorem.

$$\frac{n-1}{2(l-1)d}\leq f_i(X)\leq\frac{n-1}{2(l-1)c}. \tag{10}$$

□

## 4 MDMD with Inactive State

### 4.1 Time-Constant Activeness

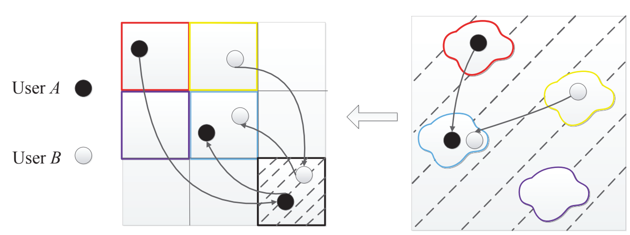



Fig. 6. Illustration in terms of addressing a specific state, in which the user is not in any PoI.

Section 3 proposes an efficient message dissemination strategy for minimizing delivery delay (MDMD) in DTNs. However, the users of MDMD are assumed to be active for all the time. In this subsection, we enhance the MDMD by adding the inactive state, which is

① http://en.wikipedia.org/wiki/Intermediate_value_theorem, June 2017.

illustrated in Fig. 6. There is a specific grid, which represents the specific situation that, users not only transit among different PoIs, but also transit to an inactive state (the way between PoIs), where users can not disseminate messages to anyone else.

Therefore, different from the previous assumptions, there is one specific state among different PoIs, which means that the states of users can be divided into two parts: the first part is active states: $\varepsilon_a = \{e_1, e_2, \cdots, e_{n-1}\}$, the second part is the inactive state: $\varepsilon_o = \{e_n\}$. The other assumptions and descriptions are identical with those of Section 3, and then we define the absorb state of the two users as $D' = \{(k,k); e_k \in \varepsilon_a\}$. When users $A$ and $B$ enter the absorb state, it means that user $A$ and user $B$ meet each other in the same PoI. We also define the earliest time for users $A$ and $B$ to meet each other as follows: $T' = inf\{t \geq 0; X_t = Y_t\}$, which means the minimal nonnegative value $t$, satisfying $X_t = Y_t$. Given the initial states of user $A$ and user $B$: $(i,j) \notin D'$, the purpose is to find the expectation of $T'$: $E_{ij}(T')$, and the distribution of $T'$.

We define $\xi^A$ as the user $A$'s first transition time from the current PoI to another one, and $\xi^B$ is defined as the user $B$'s first transiting time. We also define $\xi = \min\{\xi^A, \xi^B\}$ as the minimal transition time between user $A$ and user $B$. This is done according to the previous assumptions, and then $\xi \sim \exp(c_1 + c_2)$ remains valid, which is similar to Theorem 1.

**Theorem 7.** $\xi^A \sim \exp(c_1)$, $\xi^B \sim \exp(c_2)$, *according to the different initial states of user A and user B, the earliest time for A and B to meet each other* ($T' = \inf\{t \geq 0; X_t = Y_t\}$) *satisfies the exponential distribution with the parameter of* $\frac{1}{\alpha_1}$, $\frac{1}{\alpha_2}$, $\frac{1}{\alpha_3}$, $\frac{1}{\alpha_4}$, *respectively. Furthermore, the expectation of* $T'$ *can be approximate to* $\frac{c_1^2+c_2^2+n^2c_1c_2}{nc_1c_2(c_1+c_2)}$.

The proof of Theorem 7 is shown in Appendix $A4$. Theorem 7 shows the distribution of the expectation time for the first meeting of $A$ and $B$, when an inactive state exists.

Similar to previous descriptions, $T_1'$, $T_2'$, $T_3'$, $\cdots$, $T_{l-1}'$ are used to represent the first meeting time between user $l$ and user 1, 2, 3, $\cdots$, $l-1$, respectively. According to Theorem 7, $T_i' \sim \exp(\frac{nc_1c_2(c_1+c_2)}{c_1^2+c_2^2+n^2c_1c_2})$ is achieved. In order to simplify the expression regarding the parameter of exponential distribution, we make the following symbolic representations: $\lambda_{l,1}' = \frac{nc_lc_1(c_l+c_1)}{c_l^2+c_1^2+n^2c_lc_1}$, $\cdots$, $\lambda_{l,l-1}' = \frac{nc_lc_{l-1}(c_l+c_{l-1})}{c_l^2+c_{l-1}^2+n^2c_lc_{l-1}}$. It is not difficult to find that if we use $T'$ and $\lambda'$ to replace $T$ and $\lambda$, respectively, Theorems 3 and 4 are still available.

**Theorem 8.** *If* $c_i > c_j$, *then* $\lambda_{l,i}' > \lambda_{l,j}'$.

*Proof.* $\lambda_{l,x}'$ can be regarded as a function of $c_x$, the derivation of $\lambda_{l,x}'$ in terms of $c_x$ is shown as (11).

$$\frac{\mathrm{d}\lambda_{l,x}'}{\mathrm{d}c_x} = \frac{nc_l^2(n^2-1) + 2nc_l^3c_x + nc_l^4}{(c_l^2 + c_x^2 + n^2c_lc_x)^2} > 0. \quad (11)$$

Therefore, we can regard $\lambda_{l,i}'$ as $\lambda_{l,i}$, and Theorem 5 is still available even if there is an inactive state in the network environment. We also achieve the optimal dissemination strategy for minimizing dissemination delay.

□

**Table 2.** Simulation Parameters

| Parameter | Value | |
|---|---|---|
| | Time-Constant | Time-Varying |
| Simulation Time | 2000s | |
| Number of Grids | 36,49,64,81,100, 121,144,169,196 | 92,94,96,98,100, 102,104,106,108 |
| Number of Users Except Destination | 9 | 9,18,27,36, 45,54,63,72 |
| Message TTL | 2000s | |

### 4.2 Time-Varying Activeness

Similar with the description of Subsection 3.5, we use $\sigma_i$ to express the first meeting time between user $i$ and anyone else. The purpose is to find the user with the minimal expectation time to meet any user of another PoI. Therefore, we need to approximatively calculate $E(\sigma_i)$, which is shown in (12).

$$\begin{aligned} E(\sigma_i) &= \sum_{k\neq i}[T_{ik}'\chi_{T_{ik}'=\sigma_i}] = \sum_{k\neq i}\frac{\lambda_{ik}'}{(\sum\limits_{k\neq i}\lambda_{ik}')^2} \\ &= \frac{1}{\sum\limits_{k\neq i}\frac{nc_ic_k(c_i+c_k)}{c_i^2+c_k^2+n^2c_ic_k}} \approx \frac{1}{\sum\limits_{k\neq i}\frac{n\frac{c_i^2+c_k^2}{2}(c_i+c_k)}{c_i^2+c_k^2+n^2\frac{c_i^2+c_k^2}{2}}} \\ &= \frac{1}{\sum\limits_{k\neq i}\frac{n(c_i+c_k)}{n^2+2}} = \frac{\frac{n^2+2}{n}}{(l-2)c_i + \sum\limits_k c_k}. \end{aligned} \quad (12)$$

Therefore, Theorem 6 is also available, we just need to change $n-1$ into $\frac{n^2+2}{n}$. In conclusion, when a user's activeness is time-varying and there is an inactive state, we can also make the dissemination decision through the solution $X$, in order to minimize the dissemination delay.

## 5 Performance Evaluation

### 5.1 Simulation Settings

To demonstrate the performance of the proposed MDMD, a multi-paradigm numerical computing environment MATLAB is employed in this paper. We carry out simulations with the synthetic user's activeness. Then, two scenarios (time-constant activeness and time-varying activeness) are both considered in this paper. In the first scenario, each user has a constant activeness, which means that the activeness never changes. While in the second scenario, the user's activeness is a periodic function transiting between a upper bound and a lower bound. The results in the figures come from the average value of 500 simulation runs. The detailed simulation parameters of the above two scenarios are given in Table 2.

While a range of data is gathered from the simulations, on the premise that the delivery ratio is guaranteed to be 100% by the sufficient simulation time, we take the following two performance metrics into consideration:

1) average delay, which is the average elapsed time of the successfully-delivered messages;

2) average hopcounts, which is the average number of hops required for a message to reach the destination node.

### 5.2 Simulation Results under Time-Constant Activeness

In the first part of the simulations, we assign the time-constant activeness to each user. The DTN environment composed of 10 users (nodes) is considered. Their priorities of the activeness are scheduled as follows: $c_1 = 1.0$, $c_2 = 0.9$, $c_3 = 0.8$, $\cdots$, $c_9 = 0.2$, $c_{10} = 0.1$. User 1 is regarded as the destination and user 10 is assigned as the initial message holder. Theorem 5 is compared against other strategies and proven through testing three different dissemination priorities, which is shown in Fig. 7. MDMD is the optimal strategy proposed in this paper; FC (FirstContact) is a random dissemination strategy, which disseminates the message to a random encounter; EO (ExchangeOrder) is a variation of MDMD, which randomly exchanges two users' priorities from the original order. The changes of average delay and average hopcounts along with growth of number of grids are tested in order to compare their performances.

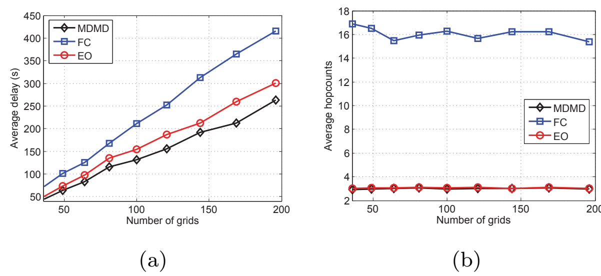



Fig. 7. Average delay and average hopcounts as a function of number of grids when the user's activeness is time-constant. (a) Average delay. (b) Average hopcounts.

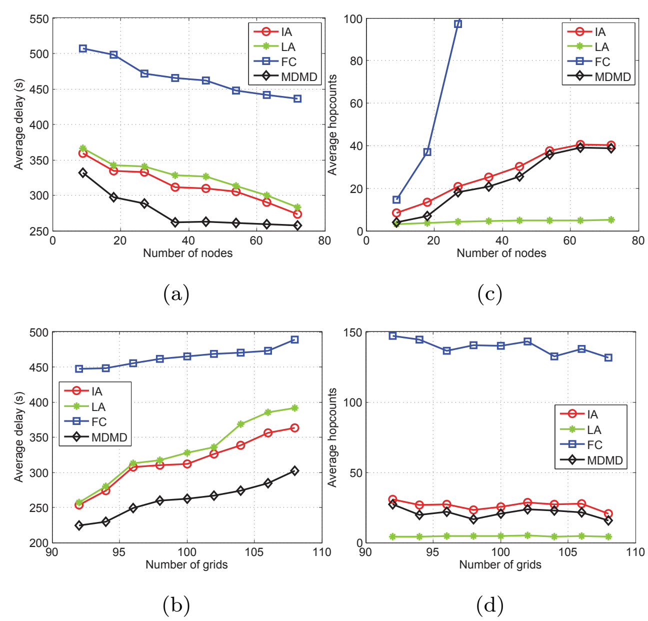



Fig. 8. The changes of average delay and average hopcounts along with the growth of number of users, and number of girds in the first group of simulations. Simulation results are under time-varying activeness.

As can be seen in Fig. 7(a), MDMD actually achieves the lowest average delay compared with other two dissemination strategies, which further proves Theorem 5. Therefore, in order to minimize dissemination delay, the optimal solution is to disseminate the message to the user with the highest activeness. Fig. 7(b) shows the changes in average hopcounts over the number of grids from 36 to 196. The simulation results show that, under time-constant activeness, MDMD achieves similar average hopcounts compared with EO, while far lower than the average hopcounts of FC.

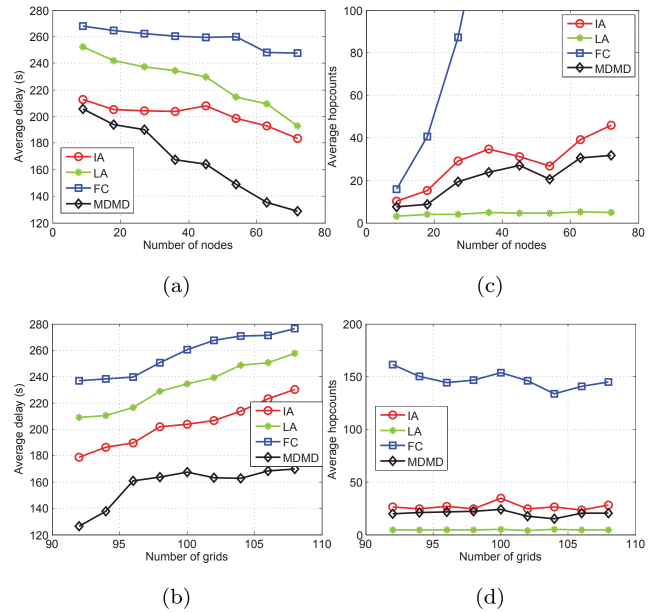



Fig. 9. The changes of average delay and average hopcounts along with the growth of number of users, and number of girds in the second group of simulations. Simulation results are under time-varying activeness.

### 5.3 Simulation Results under Time-Varying Activeness

In the second part of the simulations, we assign the time-varying activeness to each user. Three groups of simulations are tested according to the different upper and lower bounds of users' activeness. The changes of average delay and average hopcounts along with the growth of number of users and number of grids, are tested in order to compare the following four strategies: 1) MDMD, which is the strategy proposed in Subsection 3.5. 2) IA, which disseminates the message according to instantaneous activeness. 3) LA, which disseminates the message according to long-term average activeness. (4) FC, which is previously mentioned in Subsection 4.2.

For the first group of simulations, we set the number of users as 36, the users are equably divided into 9 groups. The activeness of first user group changes in the range [0.01, 0.91], the second user group is [0.02, 0.92], in a similar fashion, and the ninth user group changes in the range [0.09, 0.99]. They have the same transition period, while their initial time is not synchronous. We also set the number of grids as 100. The trends of average delay and average hopcounts along with the change of number of users and number of grids are shown from Fig. 8(a) to Fig. 8(d), respectively.

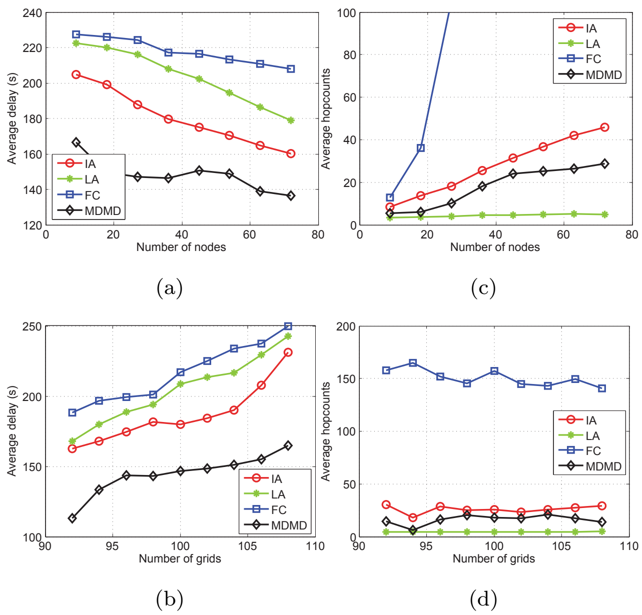



Fig. 10. The changes of average delay and average hopcounts along with the growth of number of users, and number of girds in the third group of simulations. Simulation results are under time-varying activeness.

As can be seen in Fig. 8(a) and Fig. 8(b), the MDMD proposed in this paper achieves the lowest average delay when compared with the other three dissemination strategies. Moreover, there is a downward trend of average delay along with the growth of the number of users, which indicates that more users result in a lower delivery delay. However, there is a reasonable upward trend in terms of average delay along with the growth of the number of grids, due to the fact that more girds lead to longer delivery delay. Fig. 8(c) and Fig. 8(d) display the performance of the average hopcounts. MDMD achieves similar average hopcounts compared with IA. In addition, LA achieves the lowest average hopcounts. In the analysis, there are a total of 9 groups of users. The users in the same group have the same long-term average activeness, which reduces the average hopcounts of the successfully delivered messages. However, the result is acceptable due to the reason that MDMD achieves the optimal delay performance.

For the second group of simulations, we set users' upper bounds of activeness as 0.81, 0.82, $\cdots$, 0.89, respectively. Their lower bounds of activeness are 0.11, 0.12, $\cdots$, 0.19. The other settings are similar to the first group of simulations. The trends of average delay, and average hopcounts change along with number of users, and number of grids are shown from Fig. 9(a) to Fig. 9(d), respectively, and the simulation results are under time-varying activeness. For the third group of simulations, we set users' upper bounds of activeness as 0.71, 0.72, $\cdots$, 0.79, respectively. Their lower bounds of activeness are 0.21, 0.22, $\cdots$, 0.29. The trends of average delay, and average hopcounts change along with the number of users and number of grids are shown from Fig. 10(a) to Fig. 10(d), respectively, and the simulation results are also under time-varying activeness..

The simulation results of the second and third groups are similar to the results of the first group. MDMD still achieves the lowest average delay compared with the other three dissemination strategies. Therefore, we can make the following conclusion: MDMD always achieves the lowest average delay in different levels of user activeness, when the activeness is time-varying. The simulation results further prove that the proposed efficient message dissemination strategy actually minimizes the dissemination delay. However, MDMD does not achieve the lowest average hopcounts compared with LA; this is due to the reason that MDMD successfully utilizes the opportunities to disseminate the message to the user who has the minimal expectation time of meeting anyone else. Therefore, the average hopcounts of MDMD are higher than those of LA. In conclusion, in different levels of user activeness, MDMD obtains the lowest average delay, and similar average hopcounts regarding different numbers of users, and number of grids, compared with the other three dissemination strategies in DTNs.

### 5.4 Simulation Results of the MDMD with Inactive State

In order to further prove the applicability of the proposed MDMD, we improve the MDMD for addressing the situation with an inactive state. There is no difference between the active state and the inactive state except for the communication condition, which means that two users within the inactive state can not communicate with each other.

The simulation settings are identical with the previous descriptions. The only difference is that we use an inactive state to replace an active state of the original settings, while the total number of states does not change. Then, two scenarios (time-constant activeness and time-varying activeness) are also considered in this subsection. The results in the figures come from the average value of 500 simulation runs. On the premise that the delivery ratio is guaranteed to be 100% by the sufficient simulation time, we still take the two performance metrics (average delay and average hopcounts) into consideration.

In the first part of the simulations, we assign the time-constant activeness to each user. The other settings are identical with those in Subsection 5.2. The changes of average delay, and average hopcounts along with the growth of the number of grids, are tested in order to compare their performances, which are shown in Fig. 11. .

In the second part of the simulations, we assign the time-varying activeness to each user. Three groups of simulations are tested according to the different upper and lower bounds of user activeness. The average delay and average hopcounts change along with the growth of number of users and number of grids are. Simulation results are shown in Fig. 12, Fig. 13, and Fig. 14, respectively.

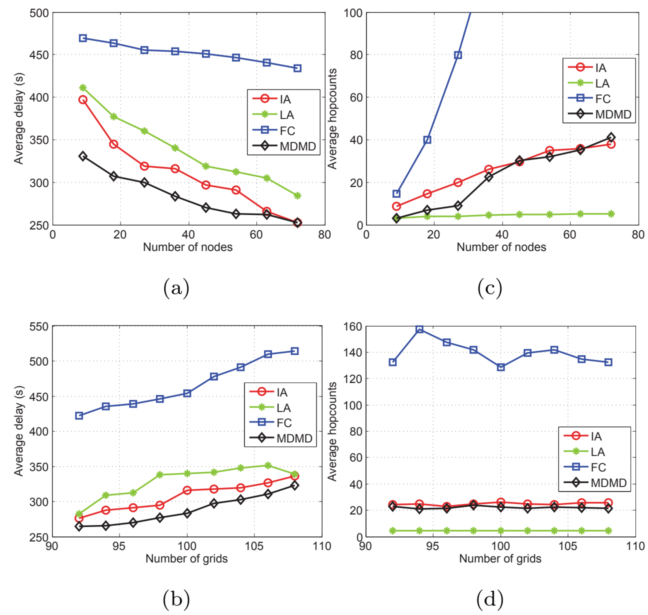



Fig. 12. The changes of average delay and average hopcounts along with the growth of number of users, and number of girds when the user's activeness is time-varying in the frist group of simulations. The simulation results are with inactive state. (a) Average delay. (b) Average hopcounts.

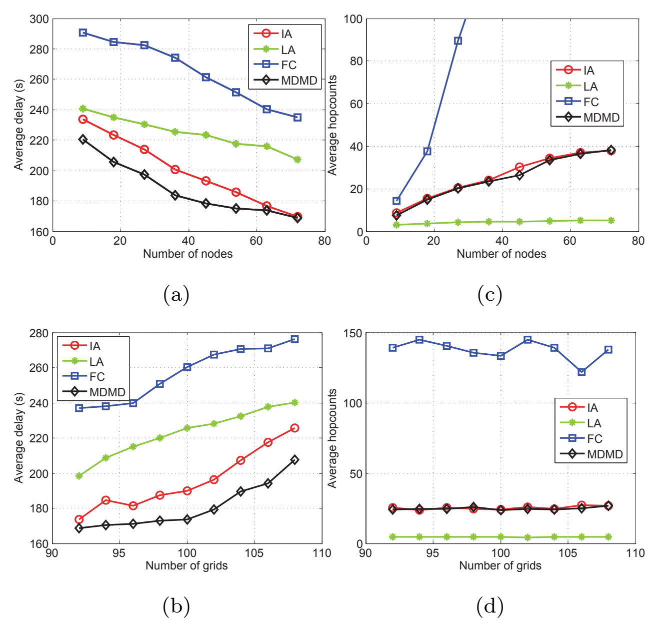



Fig. 13. The changes of average delay and average hopcounts along with the growth of number of users, and number of girds when the user's activeness is time-varying in the second group of simulations. The simulation results are with inactive state. (a) Average delay. (b) Average hopcounts.

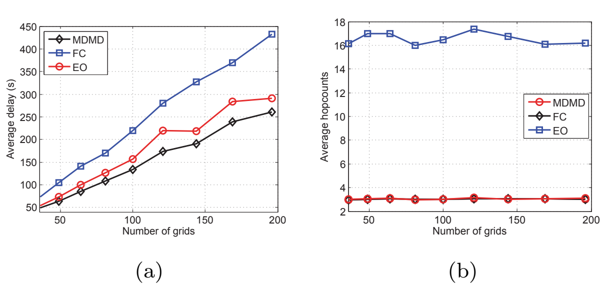



Fig. 11. The changes of average delay and average hopcounts along with the growth of number of grids when the user's activeness is time-constant. The simulation results are with inactive state. (a) Average delay. (b) Average hopcounts.

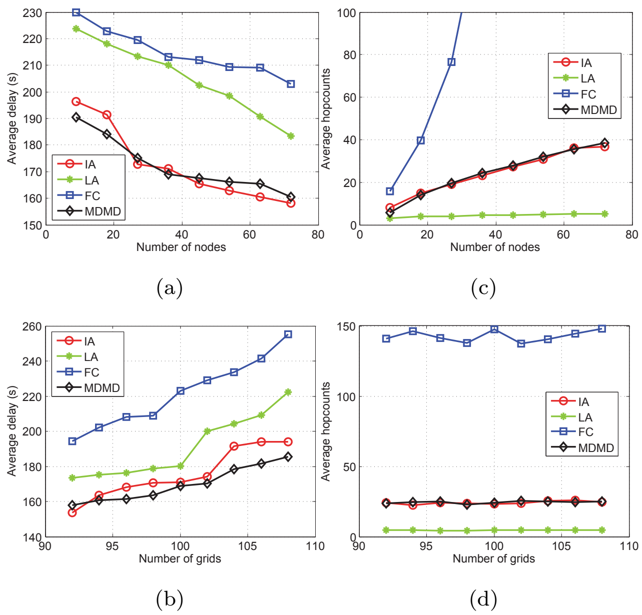



Fig. 14. The changes of average delay and average hopcounts along with the growth of number of users, and number of girds when the user's activeness is time-varying in the third group of simulations. The simulation results are with inactive state. (a) Average delay. (b) Average hopcounts.

### 5.5 Simulation Results in *random-waypoint* Mobility Pattern

In order to prove that the proposed scheme achieves a good performance in the random-waypoint mobility pattern, we test the average delay and hopcounts under the different numbers of nodes and grids. The compared methods include the previous MDMD, FC, and also PD, which is proposed in [23]. For PD, the forwarding metric is decided by a delivery predictability metric, that should reflect the probability of encountering a certain node. The simulation results are shown in Fig.15. MDMD always achieves the lowest average delay and also a comparable average hopcounts.

### 5.6 Simulation Results in Real Trace *roma/taxi*

In order to further prove that, the proposed scheme achieves a better performance compared with the other related work, we have done the simulations in the real world trace, *roma/taxi*, which includes 320 taxi drivers that work in the center of Rome, Italy. The traces present the positions of drivers. Each taxi driver has a tablet that periodically retrieves a GPS position and sends it to a central server. In order to further prove the efficiency of MDMD, simulations are done on the real trace *roma/taxi* simulations can prove that the forwarding metric proposed in MDMD achieves a better performance.

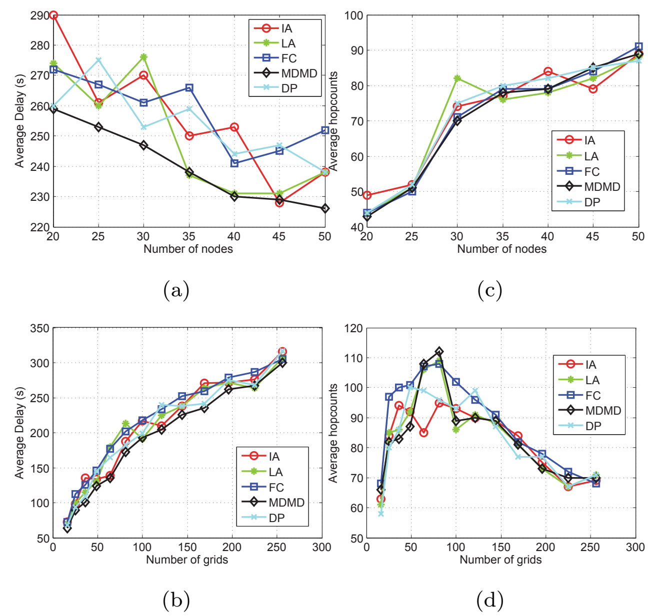
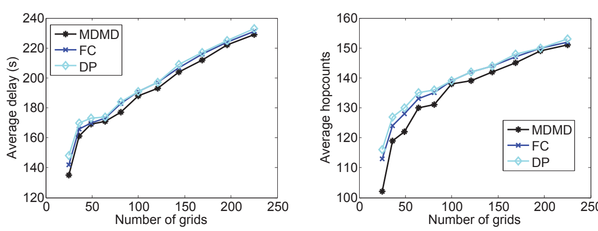



Fig. 15. The changes of average delay and average hopcounts along with the growth of number of users, and number of girds in *Random-Waypoint* mobility pattern.

As shown in Fig.16, MDMD still achieves the lowest average delay compared with the other dissemination strategies. Therefore, we can make the following conclusion: MDMD always achieves the lowest average delay even in the real trace *roma/taxi*. It is worth noting that, along with the growth of the number of girds, the average delay and hopcounts appear to be an upward trend, and this is reasonable because a large number of grids lead to a long delay. Moreover, we divide the map into 4×4, 8×8 and 16×16 grids, respectively, and test the average delay and hopcounts in the different users' activeness (as shown in Fig.17). The simulation results show that MDMD still achieves the lowest delay and hopcounts performances.

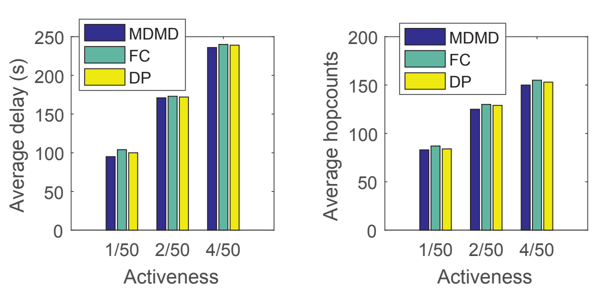
Then, in the second part, in order to test the performance of the forwarding strategy MDMD-R, which replicates the message copies to a better node with a higher forwarding metric in MDMD, we change the strategies from a single copy to the multi-copies. In other words, when a node encounters a better node, it replicates the message to the better node (with a copy in its own buffer). Then three forwarding strategies: MDMD-R, FC-R and PD-R are tested in Fig.18. Simulation results show that, MDMD-R still achieves the lowest delay and hopcounts performances, which proves that the proposed forwarding strategy in this paper is better than the other two strategies.

Finally, in order to compare the work in this paper with the related work of buffer management, we test the performances of MDMD-R and also the DTN routing protocols: Epidemic and Spray and Wait [9], which are sensitive to buffer space. Along with the growth of buffer space, three routing protocols: MDMD-R, Epidemic and Spray and Wait (initial copy number=4) are tested in Fig.19. Simulation results show that, MDMD-R still achieves the lowest delay and comparable hopcounts performance, which proves that the proposed forwarding strategy in this paper is better than the other two strategies in terms of buffer management.



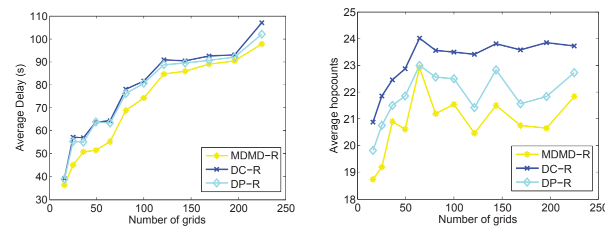

(a) (b)

Fig. 16. The changes of average delay and average hopcounts along with the growth of number of grids in the real trace *roma/taxi*. (a) Average delay. (b) Average hopcounts.



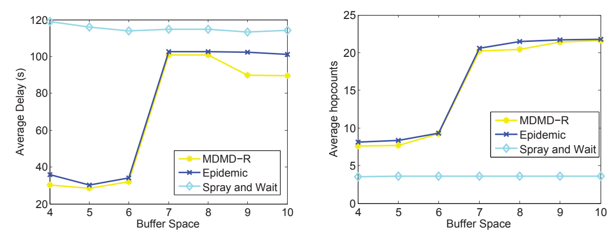

(a) (b)

Fig. 17. The changes of average delay and average hopcounts along with the growth of user's activeness. (a) Average delay. (b) Average hopcounts.




(a) (b)

Fig. 18. The changes of average delay and average hopcounts along with the growth of number of grids for replication-based strategies in the real trace *roma/taxi*. (a) Average delay. (b) Average hopcounts.




(a) (b)

Fig. 19. The changes of average delay and average hopcounts along with the growth of buffer space in the real trace *roma/taxi*. (a) Average delay, (b) Average hopcounts.

## 6 Conclusions

In order to solve the message dissemination problem, we proposed an efficient message dissemination scheme for minimizing delivery delay in DTNs (MDMD). Our main finds are listed as follows: we first defined users' activeness according to the transit habit among different PoIs. Furthermore, based on the continuous-time markov chains, an optimal user with the highest activeness is selected to assist in disseminating the message. Moreover, the situation in which that the user's activeness is time-varying is also considered. We achieved time-constant MDMD and time-varying MDMD message dissemination strategies. Finally, the enhanced MDMD by considering inactive state is further proposed to enhance the applicability. We conducted simulations in MATLAB with synthetic user's activeness. Simulation results show that, compared with other dissemination strategies, MDMD achieves the lowest average delay, and lower average hopcounts, on the premise that the delivery ratio is guaranteed to be 100% by the sufficient simulation time.

## Appendix

### A1 Proof of Theorem 1

Due to the reason that $\xi = \min\{\xi^X, \xi^Y\}$, therefore, $\xi > t$ only when $\xi^X > t$ and $\xi^Y > t$. Furthermore, the derivation result of (13) shows that $\xi \sim \exp(c_1 + c_2)$.

$$\begin{aligned} P(\xi > t) &= P(\xi^X > t \cap \xi^Y > t) \\ &= P(\xi^X > t)P(\xi^Y > t) \\ &= e^{-c_1 t} e^{-c_2 t} = e^{-(c_1+c_2)t}. \end{aligned} \tag{13}$$

### A2 Proof of Theorem 2

Consider that $X_0 = i$ and $Y_o = j$, $\xi$ is the minimal transition time between users $A$ and $B$. Therefore, after the transiting of either $A$ or $B$, the states of $A$ and $B$ change from $i$ and $j$ to $g$ and $k$, which is expressed as $(i, j) \to (g, k)$. $D$ is defined as the absorb state of $A$ and $B$, which is shown as: $D = \{(k, k), e_k \in e\}$. When $A$ and $B$ enter the absorb state, it illustrates that user $A$ and user $B$ meet each other in the same PoI. Moreover, it is not difficult to find that $(i, j) \notin D$. Otherwise, the expectation time for the first meeting of $A$ and $B$ is 0. In addition, after the first transition $(i, j) \to (g, k)$, if $(g, k) \in D$, then $T = \xi$. Otherwise, $(g, k) \notin D$, then user $A$ and user $B$ calculate the expectation of the first meeting time afresh with the initial states of $g$ and $k$. According to the above discussion, (14) is achieved.

$$\begin{aligned} E_{ij}(T) = E_{ij}(\xi) &+ \sum_{(g,k)\notin D} P((i,j) \to (g,k)) E_{gk}(T) \\ &+ \sum_{(g,k)\in D} P((i,j) \to (g,k)) \times 0. \end{aligned} \tag{14}$$

In order to simplify symbolic representation, we define $\alpha = E_{ij}(T)$. This is for the reason that there is no difference among all the PoIs, therefore, $\alpha = E_{ij}(T) = E_{gk}(T)$. We also use discrete-time combination state $Z_t$ to express the states of $A$ and $B$: $Z_t = (X_t + Y_t)$, which means that $\overline{X_0} = i$, $\overline{Y_0} = j$, then $\overline{Z_0} = (i, j)$. According to (14) and $E_{ij}(\xi) = \frac{1}{c_1+c_2}$, (15) is achieved. Furthermore, the final equation in terms of $\alpha$ is shown in (16)

$$\alpha = \frac{1}{c_1 + c_2} + \sum_{(g,k)\notin D} P(\overline{Z_1} = (g,k) | \overline{Z_0} = (i,j))\alpha. \tag{15}$$

$$\alpha = \frac{1}{c_1 + c_2} \frac{1}{1 - \sum\limits_{(g,k)\notin D} P(\overline{Z_1} = (g,k) | \overline{Z_0} = (i,j))}. \tag{16}$$

Next, we consider the Kronecker sum[2] $\boldsymbol{Z}$ of matrixes $\boldsymbol{A}$ and $\boldsymbol{B}$, which is the matrix sum defined by (17), where $\oplus$ is Kronecker sum operation, while $\otimes$ is Kronecker product operation[3]. In order to calculate $\alpha$, the matrix $\boldsymbol{Z}$ is used to achieve the transition probability from $(i, j)$ to $(g, k)$ in terms of the states of $\boldsymbol{A}$ and $\boldsymbol{B}$.

$$\begin{aligned} \boldsymbol{Z} = \boldsymbol{A} \oplus \boldsymbol{B} &= \boldsymbol{A} \otimes \boldsymbol{I} + \boldsymbol{I} \otimes \boldsymbol{B} \\ &= (\boldsymbol{A} \otimes \boldsymbol{I} + \boldsymbol{I} \otimes \boldsymbol{B})_{(i,j)(g,k)} \\ &= \boldsymbol{A}_{ig} S_{jk} + S_{ig} \boldsymbol{B}_{jk}. \end{aligned} \tag{17}$$

The problem changes into solving the matrix $\boldsymbol{Z}$, where $S_{jk}$ is defined as $S_{jk} = \begin{cases} 1 & \text{if } j = k \\ 0 & \text{if } j \neq k \end{cases}$. Similarly, $S_{ig} = \begin{cases} 1 & \text{if } i = g \\ 0 & \text{if } i \neq g \end{cases}$. The following four cases are considered in order to calculate matrix $Z$.

- Case 1: if $(g, k) = (i, j)$, then $Z = A_{ig} + B_{jk} = -(c_1 + c_2)$
- Case 2: if $(g, k) \neq (i, j)$ and $j = k$, $i \neq g$, then $Z = A_{ig} = \frac{c_1}{n-1}$
- Case 3: if $(g, k) \neq (i, j)$ and $j \neq k$, $i = g$, then $Z = B_{jk} = \frac{c_2}{n-1}$
- Case 4: other situations, $Z = 0$

Based on the above four cases, (18) is obtained. The value of $\alpha$ is further calculated through (19).

[2] http://proofwiki.org/wiki/Definition:Kronecker_Sum.
[3] http://en.wikipedia.org/wiki/Tensor_product.

$$\sum_{(g,k)\notin D} P(\overline{Z_1}=(g,k)|\overline{Z_0}=(i,j)) \\ =\frac{(n-2)c_1}{n-1}\frac{1}{c_1+c_2}+\frac{(n-2)c_2}{n-1}\frac{1}{c_1+c_2} \\ =\frac{n-2}{n-1}. \quad (18)$$

$$\alpha=(n-1)\frac{1}{c_1+c_2}. \quad (19)$$

Combining (14) and Strong Markov property④, we get the following equation:

$$E_{ij}(e^{-sT})=E_{ij}(e^{-s\xi})\sum_{(g,k)\notin D}P((i,j)\to(g,k))E_{gk}(e^{-sT})+ \\ E_{ij}(e^{-s\xi})\sum_{(g,k)\in D}P((i,j)\to(g,k)), \quad (20)$$

where $E_{ij}(e^{-s\xi})$ satisfies (21).

$$E_{ij}(e^{-s\xi})=\int_0^\infty e^{-st}(c_1+c_2)e^{-(c_1+c_2)t}\mathrm{d}t \\ =\frac{c_1+c_2}{c_1+c_2+s}. \quad (21)$$

In order to simplify symbolic representation, we define that $\beta=E_{ij}(e^{-sT})$. Combining $\beta=E_{ij}(e^{-sT})$ and (20), we get the equation of $\beta$ as (22).

$$\beta=\frac{c_1+c_2}{c_1+c_2+s}[(1-\frac{1}{n-1})\beta+\frac{1}{n-1}]. \quad (22)$$

Next, through solving (22), we obtain the final expression of $\beta$, which is shown in (23). Therefore, $T\sim\exp(\frac{c_1+c_2}{n-1})$ is achieved through the method similar to that of (21). Theorem 2 is proved.

$$\beta=\frac{\frac{c_1+c_2}{n-1}}{\frac{c_1+c_2}{n-1}+s}. \quad (23)$$

## A3 Proof of Theorem 5

First, we attempt to prove the following result: $r_k>r_{k-1}$, $\forall\ k\in(1,2,3\cdots,l)$. It is known that $r_k$ represents the delivery delay for a message from $c_k$ to $c_1$, and $c_1>c_2>\cdots>c_k$. There exist two situations according to the difference of the first dissemination step. For the first situation: the message is disseminated to $c_{k-1}$, assuming that the time of the first step is $t'$, and in the second step, the message is disseminated from $c_{k-1}$ to $c_1$, and the delay is $r_{k-1}$. Therefore, the total delay from $c_k$ to $c_1$ in the first situation is $r_k=r_{k-1}+t'>r_{k-1}$. The second situation: in the first step, the message is not disseminated to $c_{k-1}$, therefore, the system is assumed to be a $r_{k-1}$ system, where $c_1>c_2>\cdots>c_{k-2}>c_k$. Due to the reason that $c_{k-1}>c_k$, the activeness level for user $k-1$ is higher than that of user $k$. Therefore $r_k>r_{k-1}$ can also be achieved in the second situation. In conclusion, $r_k>r_{k-1}$, $\forall\ k\in(1,2,3\cdots,l)$.

Based on the above proof, we get the conclusion that $r_1<r_2<r_3<\cdots<r_l$, and $r_l$ satisfies (24).

$$r_l=\frac{1}{\lambda_{l,1}+\lambda_{l,2}+\cdots+\lambda_{l,l-1}}+\frac{\sum_{j=1}^{l-1}\lambda_{l,j}r_j}{\lambda_{l,1}+\lambda_{l,2}+\cdots+\lambda_{l,l-1}}. \quad (24)$$

If we exchange $\lambda_{l,i}$ and $\lambda_{l,j}$, the variation of $r_l$ is $(\lambda_{l,i}r_j+\lambda_{l,j}r_i)-(\lambda_{l,j}r_j+\lambda_{l,i}r_i)=(r_j-r_i)(\lambda_{l,i}-\lambda_{l,j})>0$

Therefore, $\lambda_{l,1}>\lambda_{l,2}>\cdots>\lambda_{l,l-1}$ is actually the optimal priority order, and we get the conclusion that Theorem 5 is proved.

## A4 Proof of Theorem 7

Due to the reason that the total number of states and the user's transition frequency of the enhanced MDMD are identical with that of the proposed MDMD, therefore, according to the (14), we can achieve (25). The only difference is the communication condition of user $A$ and $B$ changes from $D=\{(k,k),e_k\in e\}$ to $D'=\{(k,k);e_k\in\varepsilon_a\}$.

$$E_{ij}(T')=E_{ij}(\xi)+\sum_{(g,k)\notin D'}P((i,j)\to(g,k))E_{gk}(T') \\ +\sum_{(g,k)\in D'}P((i,j)\to(g,k))\times 0. \quad (25)$$

In order to simplify symbolic representation, we define $\alpha'=E_{ij}(T')$. According to (25), we achieve (26).

④ http://en.wikipedia.org/wiki/Markov_property.

$$\alpha' = \frac{1}{c_1 + c_2} + \sum_{(g,k)\notin D'} P((i,j) \to (g,k))\alpha'. \quad (26)$$

According to the different initial states of users $A$ and $B$, there are four cases in terms of $P((i,j) \to (g,k))$, which are shown as follows.

- Case 1: $\sum_{(g,k)\in D'} P((i,j) \to (g,k)) = \frac{1}{n-1}$, when $(i,j) \notin D', i,j \in \varepsilon_a$.
- Case 2: $\sum_{(g,k)\in D'} P((i,j) \to (g,k)) = \frac{c_2}{(n-1)(c_1+c_2)}$, when $(i,j) \notin D', i \in \varepsilon_a, j \in \varepsilon_o$.
- Case 3: $\sum_{(g,k)\in D'} P((i,j) \to (g,k)) = \frac{c_1}{(n-1)(c_1+c_2)}$, when $(i,j) \notin D', i \in \varepsilon_o, j \in \varepsilon_a$.
- Case 4: $\sum_{(g,k)\in D'} P((i,j) \to (g,k)) = 0$, when $(i,j) \notin D', i j \in \varepsilon_o$.

Then, in different cases, we achieve the final expressions of $\sum_{(g,k)\notin D'} P((i,j) \to (g,k))$ as follows.

$$\sum_{(g,k)\notin D'} P((i,j)\to(g,k)) = \begin{cases} \frac{n-2}{n-1}, \text{if in case 1.} \\ \frac{(n-1)(c_1+c_2)-c_2}{(n-1)(c_1+c_2)}, \text{if in case 2.} \\ \frac{(n-1)(c_1+c_2)-c_1}{(n-1)(c_1+c_2)}, \text{if in case 3.} \\ 1, \text{if in case 4.} \end{cases}$$

According to the different initial states of users $A$ and $B$, $\alpha' = E_{ij}(T')$ can be expressed as $\alpha'_{aa}$, $\alpha'_{ao}$, $\alpha'_{oa}$, $\alpha'_{oo}$, respectively, which are shown as follows.

$$\alpha' = E_{ij}(T') = \begin{cases} \alpha'_{aa}, \text{if } i \in \varepsilon_a, j \in \varepsilon_a, (i,j) \notin D'. \\ \alpha'_{ao}, \text{if } i \in \varepsilon_a, j \in \varepsilon_o, (i,j) \notin D'. \\ \alpha'_{oa}, \text{if } i \in \varepsilon_o, j \in \varepsilon_a, (i,j) \notin D'. \\ \alpha'_{oo}, \text{if } i \in \varepsilon_o, j \in \varepsilon_o, (i,j) \notin D'. \end{cases}$$

According to the different states of $(g,k)$, $\alpha'_{aa}$ can be expressed as (27). Similarly, $\alpha'_{ao}$, $\alpha'_{oa}$ and $\alpha'_{oo}$ also can be achieved through the transition matrix $\boldsymbol{H}$, which is shown in (28).

$$\begin{aligned} \alpha'_{aa} = \frac{1}{c_1+c_2} &+ \sum_{(g,k)\notin D', (g,k)=(a,a)} P((a,a) \to (g,k))\alpha'_{aa} \\ &+ \sum_{(g,k)\notin D', (g,k)=(a,o)} P((a,a) \to (g,k))\alpha'_{ao} \\ &+ \sum_{(g,k)\notin D', (g,k)=(o,a)} P((a,a) \to (g,k))\alpha'_{oa} \\ &+ \sum_{(g,k)\notin D', (g,k)=(o,o)} P((a,a) \to (g,k))\alpha'_{oo}. \end{aligned} \quad (27)$$

$$\boldsymbol{H} = \begin{pmatrix} h(aa,aa) & h(ao,aa) & h(oa,aa) & h(oo,aa) \\ h(aa,ao) & h(ao,ao) & h(oa,ao) & h(oo,ao) \\ h(aa,oa) & h(ao,oa) & h(oa,oa) & h(oo,oa) \\ h(aa,oo) & h(ao,oo) & h(oa,oo) & h(oo,oo) \end{pmatrix}. \quad (28)$$

In the transition matrix $\boldsymbol{H}$, $h(aa,aa)$ means $P((a,a) \to (a,a))$, the others are similar to $h(aa,aa)$. Therefore, the transition matrix $\boldsymbol{H}$ can be expressed as (29).

$$\boldsymbol{H} = \begin{pmatrix} \frac{n-3}{n-1} & \frac{(n-2)c_2}{(n-1)(c_1+c_2)} & \frac{(n-2)c_1}{(n-1)(c_1+c_2)} & 0 \\ \frac{c_2}{(n-1)(c_1+c_2)} & \frac{(n-2)c_1}{(n-1)(c_1+c_2)} & 0 & \frac{c_1}{(c_1+c_2)} \\ \frac{c_1}{(n-1)(c_1+c_2)} & 0 & \frac{(n-2)c_2}{(n-1)(c_1+c_2)} & \frac{c_2}{(c_1+c_2)} \\ 0 & \frac{c_1}{(n-1)(c_1+c_2)} & \frac{c_2}{(n-1)(c_1+c_2)} & 0 \end{pmatrix}. \quad (29)$$

We use $\alpha_1$, $\alpha_2$, $\alpha_3$, $\alpha_4$ to express $\alpha'_{aa}$, $\alpha'_{ao}$, $\alpha'_{oa}$, $\alpha'_{oo}$, respectively. Therefore, we can achieve the following equation:

$$\alpha' = \boldsymbol{H}\alpha' + d_1, \quad (30)$$

where $\alpha' = (\alpha_1\ \alpha_2\ \alpha_3\ \alpha_4)^{\mathrm{T}}$, $\boldsymbol{H}$ has already been calculated, and $d_1 = [\frac{1}{c_1+c_2}\ \frac{1}{c_1+c_2}\ \frac{1}{c_1+c_2}\ \frac{1}{c_1+c_2}]^{\mathrm{T}}$. Through solving (30), we obtain the final equations of $\alpha_1$, $\alpha_2$, $\alpha_3$, $\alpha_4$ as follows, respectively.

$$\alpha_1 = \frac{n}{c_1 + c_2}.$$

$$\alpha_2 = \frac{c_1 + nc_2}{c_2(c_1 + c_2)}.$$

$$\alpha_3 = \frac{c_2 + nc_1}{c_1(c_1 + c_2)}.$$

$$\alpha_4 = \frac{c_1^2 + c_2^2 + nc_1c_2}{c_1c_2(c_1 + c_2)}.$$

Combining (25) and Strong Markov property, we get the following equation (31).

$$E_{ij}(e^{-sT'}) = E_{ij}(e^{-s\xi}) \sum_{(g,k)\notin D'} P((i,j) \to (g,k)) E_{gk}(e^{-sT'}) + E_{ij}(e^{-s\xi}) \sum_{(g,k)\in D'} P((i,j) \to (g,k)). \quad (31)$$

Similar to the definition of $\alpha'$, the different cases of $\beta$ are shown as follows.

$$\beta = E_{ij}(e^{-sT'}) = \begin{cases} \beta_{aa}, \text{if } i \in \varepsilon_a, j \in \varepsilon_a, (i,j) \notin D'. \\ \beta_{ao}, \text{if } i \in \varepsilon_a, j \in \varepsilon_o, (i,j) \notin D'. \\ \beta_{oa}, \text{if } i \in \varepsilon_o, j \in \varepsilon_a, (i,j) \notin D'. \\ \beta_{oo}, \text{if } i \in \varepsilon_o, j \in \varepsilon_o, (i,j) \notin D'. \end{cases}$$

We use $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ to express $\beta_{aa}$, $\beta_{ao}$, $\beta_{oa}$, $\beta_{oo}$, respectively. Therefore, we can obtain the equation of $\beta$:

$$(\boldsymbol{I} - \phi \boldsymbol{I})\beta = \phi d_2, \quad (32)$$

where $\boldsymbol{I}$ is identity matrix, $\boldsymbol{H}$ is identical with that of (29), $\beta$ is $[\beta_1\ \beta_2\ \beta_3\ \beta_4]^{\mathrm{T}}$, $\phi = \frac{c_1+c_2}{c_1+c_2+s}$ and $d_2 = [\frac{1}{n-1}\ \frac{c_2}{(n-1)(c_1+c_2)}\ \frac{c_1}{(n-1)(c_1+c_2)}\ 0]^{\mathrm{T}}$. And then we change (32) into (33) to further solve $\beta$.

$$\begin{pmatrix} (n-3) & \frac{c_2}{(c_1+c_2)} & \frac{c_1}{(c_1+c_2)} & 0 \\ (n-2)c_2 & (n-2)c_1 & 0 & c_1 \\ (n-2)c_1 & 0 & (n-2)c_2 & c_2 \\ 0 & c_1 & c_2 & 0 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{pmatrix} = \begin{pmatrix} 1 \\ c_2 \\ c_1 \\ 0 \end{pmatrix} \quad (33)$$

Through solving (33), we obtain the final equations of $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ as follows, respectively.

$$\beta_1 = \frac{(c_1 + s)[nc_2^2 + (n-1)sc_2] + (c_2 + s)[nc_1^2 + (n-1)sc_1]}{[(n^2-1)s^2 + nc_1c_2 + ns(c_1+c_2)](c_1+c_2) + (n^2-2)sc_1c_2 + (n-1)^2s^3}.$$

$$\beta_2 = \frac{[(n-1)(c_1 + s) + nc_2](c_1 + s)c_2 + c_1^2c_2}{[(n^2-1)s^2 + nc_1c_2 + ns(c_1+c_2)](c_1+c_2) + (n^2-2)sc_1c_2 + (n-1)^2s^3}.$$

$$\beta_3 = \frac{[(n-1)(c_2 + s) + nc_1](c_2 + s)c_1 + c_2^2c_1}{[(n^2-1)s^2 + nc_1c_2 + ns(c_1+c_2)](c_1+c_2) + (n^2-2)sc_1c_2 + (n-1)^2s^3}.$$

$$\beta_4 = \frac{c_1c_2(nc_1 + nc_2 + 2ns - 2s)}{[(n^2-1)s^2 + nc_1c_2 + ns(c_1+c_2)](c_1+c_2) + (n^2-2)sc_1c_2 + (n-1)^2s^3}.$$

Similar to (23), we attempt to change $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ into the expression forms of $\frac{\lambda_1}{\lambda_1+s}$, $\frac{\lambda_2}{\lambda_2+s}$, $\frac{\lambda_3}{\lambda_3+s}$, $\frac{\lambda_4}{\lambda_4+s}$, where $\lambda_1$, $\lambda_2$, $\lambda_3$, $\lambda_4$ are the parameters of exponential distributions in terms of different initial states. The calculation results are shown as follows:

$$\lambda_1 = -\frac{c_2(c_1+s)}{(s-n(c_1+s))} - \frac{c_1(c_2+s)}{(s-n(c_2+s))}.$$

$$\lambda_2 = -\frac{c_2s(2c_1+s) - c_2n(c_1+s)(c_1+c_2+s)}{(c_1n-s+ns)(c_1-s+c_2n+ns)}.$$

$$\lambda_3 = -\frac{c_1s(2c_2+s) - c_1n(c_2+s)(c_1+c_2+s)}{(c_2n-s+ns)(c_2-s+c_1n+ns)}.$$

$$\lambda_4 = \frac{2c_1c_2s(n-1) + c_1c_2n(c_1+c_2)}{s^2(n-1)^2 + (c_1^2+c_2^2)n + s(c_1+c_2)(n^2-1) + c_1c_2n^2}.$$

According to the first order approximation, when $s \to 0$, $\lambda_1$, $\lambda_2$, $\lambda_3$, $\lambda_4$ become $\frac{1}{\alpha_1}$, $\frac{1}{\alpha_2}$, $\frac{1}{\alpha_3}$, $\frac{1}{\alpha_4}$, respectively. In addition, the probability of the case that the initial states of $A$ and $B$ are both in online states is $\frac{(n-1)^2}{n^2}$. Similarly, we can achieve the probabilities of other cases. Therefore, the expectation of $T'$ can be approximate to the following result: (34). Theorem 7 is proved.

$$E(T') = \frac{(n-1)^2}{n^2}\alpha_1 + \frac{n-1}{n^2}(\alpha_2 + \alpha_3) + \frac{1}{n^2}\alpha_4 = \frac{c_1^2 + c_2^2 + n^2c_1c_2}{nc_1c_2(c_1 + c_2)}. \quad (34)$$

**References**

[1] Burleigh S, Hooke A, Torgerson L. Delay-tolerant networking: An approach to interplanetary Internet. *IEEE Communications Magazine*, 2003, 41(6): 128-136.

[2] Wang E, Yang Y, Wu J. A Knapsack-based buffer management strategy for delay-tolerant networks. *Journal of Parallel and Distributed Computing*, 2015, 86(C): 1-15.

[3] Akyildiz I F, Akan Ö, Chen C, Fang J, Su W. InterPlaNetary Internet: State-of-the-art and research challenges. *Computer Networks*, 2003, 43(2): 75-112.

[4] Uddin M Y S, Ahmadi H, Abdelzaher T, Kravets R. Intercontact routing for energy constrained disaster response networks. *IEEE Transactions on Mobile Computing*, 2013, 12(10): 1986-1998.

[5] Juang P, Oki H, Wang Y, Martonosi M, Peh L S, Rubenstein D. Energy-efficient computing for wildlife tracking: Design tradeoffs and early experiences with ZebraNet. In *Proc. the 10th ASPLOS*. Oct. 2002, pp.96-107.

[6] Yang S, Yeo C K, Lee F B S. Cooperative duty cycling for energy-efficient contact discovery in pocket switched networks. *IEEE Transactions on Vehicular Technology*, 2013, 62(4): 1815-1826.

[7] Wu J, Wang Y. Hypercube-based multipath social feature routing in human contact networks. *IEEE Transactions on Computers*, 2014, 63(2): 383-396.

[8] Xiao M, Wu J, Huang L. Community-aware opportunistic routing in mobile social networks. *IEEE Transactions on Computers*, 2014, 63(7): 1682-1695.

[9] Zhang X, Neglia G, Kurose J, Towsley D F. Performance modeling of epidemic routing. *Computer Networks*, 2007, 51(10): 2867-2891.

[10] Erramilli V, Crovella M, Chaintreau A, Diot C. Delegation forwarding. In *Proc. the 9th ACM MobiHoc*, May 2008, pp.251-260.

[11] Dubois-Ferriere H, Grossglauser M, Vetterli M. Age matters: Efficient route discovery in mobile ad hoc networks using encounter ages. In *Proc. ACM MobiHoc 2003*, June 2003, pp.257-266.

[12] Wei K, Guo S, Zeng D, Xu K, Li K. Exploiting small world properties for message forwarding in delay tolerant networks. *IEEE Transactions on Computers*, 2015, 64(10): 2809-2818.

[13] Lu Y, Wang W, Chen L, Zhang Z, Huang A. Distance-based energy-efficient opportunistic broadcast forwarding in mobile delay-tolerant networks. *IEEE Transactions on Vehicular Technology*, 2016, 65(7): 5512-5524.

[14] Elwhishi A, Ho P H, Naik K, Shihada B. A novel message scheduling framework for delay tolerant networks routing. *IEEE Transactions on Parallel and Distributed Systems*, 2013, 24(5): 871-880.

[15] Krifa A, Barakat C, Spyropoulos T. Message drop and scheduling in DTNs: theory and practice. *IEEE Transactions on Mobile Computing*, 2012, 11(9): 1470-1483.

[16] Wang E, Yang Y, Wu J, Liu W. A buffer management strategy on spray and wait routing protocol in DTNs. In *Proc. the 44th IEEE ICPP*, Sept. 2015, pp.799-808.

[17] Huang J, Liu W, Su Y, Wang F. Multi-rate combination of partial information-based routing and adaptive modulation and coding for space deterministic delay/ disruption tolerant networks. *IET Communications*, 2017, 11(9): 1365-1370.

[18] Seregina T, Brun O, El-Azouzi R, Prabhu B J. On the design of a reward-based incentive mechanism for delay tolerant networks. *IEEE Transactions on Mobile Computing*, 2017, 16(2): 453-465.

[19] Wang R, Qiu M, Zhao K, Qian Y. Optimal RTO timer for best transmission efficiency of DTN protocol in deep-space vehicle communications. *IEEE Transactions on Vehicular Technology*, 2017, 66(3): 2536-2550.

[20] Li F, Jiang H, Li H, Cheng Y, Wang Y. SEBAR: Social-energy-based routing for mobile social delay-tolerant networks. *IEEE Transactions on Vehicular Technology*, 2017, 66(8): 7195-7206.

[21] Sabbagh A, Wang R, Zhao K, Bian D. Bundle protocol over highly asymmetric deep-space channels. *IEEE Transactions on Wireless Communications*, 2017, 16(4): 2478-2489.

[22] Sakai K, Sun M T, Ku W S, Wu J, Alanazi F S. Performance and security analyses of onion-based anonymous routing for delay tolerant networks. *IEEE Transactions on Mobile Computing*, 2017, 16(12): 3473-3487.

[23] Lindgren A, Doria A, Schelén O. Probabilistic routing in intermittently connected networks. *ACM SIGMOBILE Mobile Computing and Communications Review*, 2003, 7(3): 19-20.

[24] Zhang X, Kurose J, Levine B N, Towsley D, Zhang H. Study of a bus-based disruption-tolerant network: Mobility modeling and impact on routing. In *Proc. the 13th MobiCom*, Sept. 2007, pp.195-206.

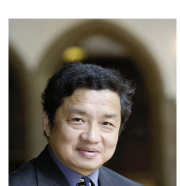
[25] Spyropoulos T, Psounis K, Raghavendra C S. Efficient routing in intermittently connected mobile networks: The multiple-copy case. *IEEE/ACM Transactions on Networking*, 2008, 16(1): 77-90.

[26] Wang E, Yang Y, Wu J, Yang W S, Liu W B. A lightweight message dissemination strategy for minimizing delay in online social networks. In *Proc. Globecom*, Dec. 2015, pp.1-6.

**En Wang** received his B.E. degree in software engineering from Jilin University, Changchun, Jilin, in 2011, his M.E. degree in computer science and technology from Jilin University, Changchun, in 2013, and his Ph.D. in computer science and technology from Jilin University, Changchun, in 2016, respectively. He is currently an associate professor in the Department of Computer Science and Technology at Jilin University, Changchun. He is also a visiting scholar in the Department of Computer and Information Sciences at Temple University in Philadelphia. His current research focuses on the efficient utilization of network resources, scheduling and drop strategy in terms of buffer-management, energy-efficient communication between human-carried devices, and mobile crowdsensing.

**Wei-Shih Yang** received his Ph.D. from Cornell University, Ithaca, New York, in 1984. He is currently a professor in the Department of Mathematics at Temple University, Philadelphia. His research interests are in the fields of probability theory, mathematical physics, mathematical finance and complex networks. He has worked on phase transitions and critical phenomena in statistical mechanics, random fields, quantum field theory, percolation, Ising model, and self-avoiding random walks. His more recent work includes quantum random walks, quantum computing, ruin probability of risk processes and wireless networks.

**Yong-Jian Yang** received his B.E. degree in automatization from Jilin University of Technology, Changchun, Jilin, in 1983, his M.E. degree in computer communication from Beijing University of Post and Telecommunications, Beijing, in 1991, and his Ph.D. in software and theory of computer from Jilin University, Changchun, Jilin, in 2005, respectively. He is currently a professor and a PhD supervisor at Jilin University, the vice dean of the Software College of Jilin University, director of Key lab under the Ministry of Information Industry, standing director of the Communication Academy, and a member of the Computer Science Academy of Jilin Province. His research interests include network intelligence management, wireless mobile communication and services, and wireless mobile communication.



**Jie Wu** received his B.S. in computer engineering and M.S. in computer science from Shanghai University of Science and Technology (now Shanghai University), Shanghai, China, in 1982 and 1985, respectively, and his Ph.D. in computer engineering from Florida Atlantic University, Boca Raton, in 1989. Jie Wu is the chair and a Laura H. Carnell Professor in the Department of Computer and Information Sciences at Temple University. Prior to joining Temple University, he was a program director at the National Science Foundation and Distinguished Professor at Florida Atlantic University. His current research interests include mobile computing and wireless networks, routing protocols, cloud and green computing, network trust and security, and social network applications. Dr. Wu regularly published in scholarly journals, conference proceedings, and books. He serves on several editorial boards, including IEEE Transactions on Computers, IEEE Transactions on Service Computing, and Journal of Parallel and Distributed Computing. Dr. Wu was general co-chair for IEEE MASS 2006 and IEEE IPDPS 2008 and program co-chair for IEEE INFOCOM 2011. Currently, he is serving as general chair for IEEE ICDCS 2013 and ACM MobiHoc 2014, and program chair for CCF CNCC 2013. He was an IEEE Computer Society Distinguished Visitor, ACM Distinguished Speaker, and chair for the IEEE Technical Committee on Distributed Processing (TCDP). Dr. Wu is a CCF Distinguished Speaker and a Fellow of the IEEE. He is the recipient of the 2011 China Computer Federation (CCF) Overseas Outstanding Achievement Award.

**Wen-Bin Liu** received his B.S. degree in physics from Jilin University, Changchun, Jilin, in 2012. He is currently a Ph.D. candidate in the Department of Computer Science and Technology, Jilin University, Changchun. His current research focuses on communications in body area networks, delay tolerant networks, and crowdsensing.