A Campus Community-based Mobility Model for Routing in Opportunistic Networks

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Abstract

Mobility models are invaluable for determining the performance of routing protocols in opportunistic networks. The movement of nodes has a significant influence on the topological structure and data transmission in networks. In this paper, we propose a new mobility model called the campus-based community mobility model (CBCNM) that closely reflects the daily life pattern of students on a real campus. Consequent on a discovery that the pause time of nodes in their community follows a power law distribution, instead of a classical exponential distribution, we abstract the semi-Markov model from the movement of the campus nodes and analyze its rationality. Then, using the semi-Markov algorithm to switch the movement of the nodes between communities, we infer the steady-state probability of node distribution at random time points. We verified the proposed CBCNM via numerical simulations and compared all the parameters with real data in several aspects, including the nodes' contact and inter-contact times. The results obtained indicate that the CBCNM is highly adaptive to an actual campus scenario. Further, the model is shown to have better data transmission network performance than conventional models under various routing strategies.

Keywords: Opportunistic network, Mobility models, Routing

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1. Introduction

Opportunistic networks [1] are wireless mobile networks that are constructed entirely from users' devices, which are carried by people, vehicles, or animals. Opportunistic networks differ from traditional ad hoc networks in several aspects: in these networks, network partitions and disconnections are very common and a fully connected path between source and destination is not guaranteed. As a consequence, routing protocols are unable to find a connected path to their destinations; instead, they exploit the contacts made by nodes to transmit messages. They use the store, carry, and forward principle—in which data are stored locally on a device, carried as the user moves, and forwarded to the next hop when there is a chance. These approaches are used to cope with and exploit the characteristics of opportunistic networks, such as the mobility pattern of the nodes and the contact and inter-contact times.

A mobility model should accurately reflect the mobility patterns of the nodes in real-world scenarios, as this has a significant impact on the delivery of messages. The same routing algorithm may exhibit different performances for features such as packet delivery ratio, end-to-end delay, and overhead, under different mobility models. In this paper, we propose a campus mobility model that focuses on the daily life traces of students on a campus, and apply it to various routing strategies. The contributions made in this paper can be summarized as follows:

1) We divide the mobility model of a campus into three sub-models according to the activities of students in different time segments. This activity was carried out following our discovery that the movements of the nodes are driven by the social relationships among them.
2) We propose a semi-Markov model-based state-switching algorithm that we utilize to model the movements of nodes on campus according to the length of time the nodes stay in their respective communities, which obeys a power law [2] instead of a classical exponential distribution.
3) We analyze the steady-state performance of the model and verify its feasibility in a campus environment. More specifically, we compare its results with real movement trace data from aspects such as node contact and inter-contact times, and show that the proposed CBCNM is highly adaptive to real traces in an actual campus scenario.
4) We compare the CBCNM with other mobility models by applying them to various routing protocols in a campus scenario.

The remainder of this paper is organized as follows. Section 2 discusses related work and briefly describes the current classification of mobility models. Section 3 outlines the proposed CBCNM for opportunistic networks. Section 4 discusses the experiments conducted and analyzes the results obtained. Section 5 concludes this paper.

2. Related Work

Mobility models are used to simulate actual human movement because such movement has an important impact on the network transmission mode and data communication efficiency. Because of the important role that mobility plays in opportunistic networks, studies geared towards understanding the mobility of nodes are actively being conducted. Another objective is to establish mobility models that are both easy to handle and able to reproduce key features of real traces. Current mobility models can be classified into two main categories: individual mobility models and group mobility models.

Individual mobility models deal primarily with the movements of independent nodes, which are completely independent of other nodes. In this case, the mobility models mainly depict the individual characteristics of the nodes. Examples of such models include random walk (RW) [3], random waypoint (RWP) [4], and random direction (RD) [5]. These models are simple and easy to build. However, their nodes are irregular and change sharply, as they may turn urgently and suddenly stop. Further, these models can present unrealistic movements and node distribution is non-uniform in the network. In fact, the actions these models simulate seldom occur in the real mobility of a human being. As a result, several modified RWP models have been proposed [6].

In group mobility models, nodes belonging to a group have similar movement characteristics, whereas nodes related to different groups have diverse mobility patterns. Typical group mobility models include CMM [8], HCMM [9] (and improved versions), reference point group mobility model (RPGM) [7], and community mobility model [10]. The main idea underlying these models is that the location, speed, and movement direction of a mobile node are affected by other nodes in the neighborhood. In recent years, social networks have been extensively studied. Researchers have also applied theoretical models to the mobility models of network nodes, such as the small world in motion (SWIM [11–13]) model—a simple mobility model that generates small worlds of mobile humans. The model is very simple to implement and very efficient in simulations. The mobility pattern of the nodes is based on a simple intuition of human mobility: people go more often to places that are close to their homes and where they can meet a lot of other people.

Most of the mobility models presented above do not capture the social properties of human mobility or only model one aspect of human mobility. Observations of campus students show that their daily lives are regular—in general, they carry out activities in fixed locations, such as classrooms, dormitories, and libraries. At various times throughout the day, students have different opportunities or interests to go to other places. The truncated levy walk (TLW) model has shown that human intentions, rather than geographical artifacts, play a major role in the production of heavy-tail tendencies [14]. By utilizing the pattern of these movements messages can therefore be transmitted more efficiently. To the best of our knowledge, only a few models are available for studying the behaviors and customs of students on a campus. Motivated by this lack, we developed a new campus community mobility model for opportunistic networks that subsumes various types of sub-models, implements switching, and realistically reproduces the daily mobility pattern of students on a campus.

3. The Campus Mobility Model

3.1 Students' Daily Activities Sub-models

Classroom or library, dormitory, and outdoor activity points are the main places for students on campus to stay throughout the day. Thus, the three sub-models in our study are representative of the regularity of student node motility on campus. **Figs. 1** and **2,** constructed from a real dataset, depict the staying time of student nodes in various places. These distributions conform to actual school life. Moreover, the number of points of interest (POIs) distributed in the different places changes over time. Consequently, we primarily consider three kinds of circumstances and divide the campus mobility model into three sub-models according to students' social activities. The resulting sub-models are shown in **Fig. 4**.

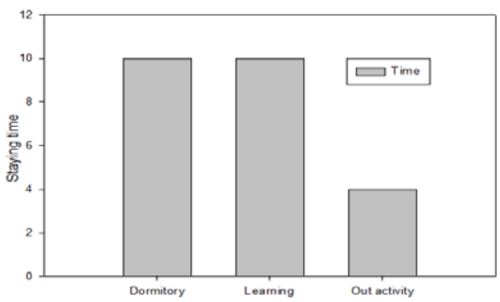


Fig. 1. Staying time in sub-models

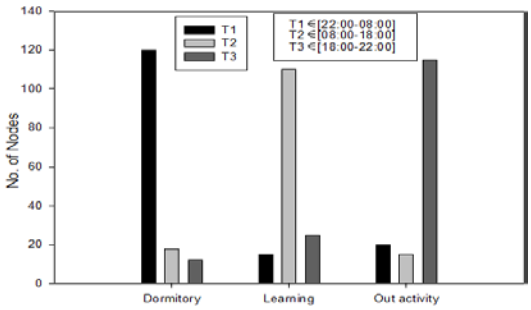


Fig. 2. Distribution of nodes in a day

3.1.1 The learning sub-model

The learning sub-model describes the learning activities of students on campus, including attending lectures in classrooms, reading and studying in libraries, and performing experiments in laboratories. These activities have the following common attributes.

1) They follow a normal distribution with an average of two hours.

2) They are fixed to a particular place with a defined number of nodes.

From **Fig. 2**, it is clear that when a node is in the learning sub-model, a coordinate is assigned randomly because the place where it stays for a period of time obeys a Gaussian distribution.

3.1.2 The dormitory sub-model

The dormitory sub-model describes the activities of students in their dormitories. Each student node on the map is assigned a fixed coordinate representing its current dormitory position. In the dormitory sub-model, two conditions are met:

1) Each node finds a path back to its dormitory position via the shortest path algorithm.

2) The staying time follows a Gaussian distribution and nodes do not leave the coordinate until they go to next sub-model.

3.1.3 The outdoor activity sub-model

The outdoor activity sub-model encapsulates after-school socializing activities. It divides student nodes into two types: outgoing students and introverted students. Outgoing students are more sociable and usually participate in social activities more frequently than introverted students.

At the beginning of the simulation, every node is assigned a POI, which indicates whether it is a more popular place, such as a supermarket near the school or a cinema. Immediately after school, the node is assigned into a collective group for outdoor activities, and they can select walking, cycling, bus, or car as their means of travel and utilize the shortest path selection algorithm to move to the meeting spots on the map.

3.2 Switching Over Between Sub-models

3.2.1 The sub-models switching algorithm

In this section, we examine the switching algorithm used with the above sub-models. A node's movement is regarded as switching of state between different sub-models and is modeled using a semi-Markov model. In addition, using the dormitory sub-model as an example, we are able to construct the chart depicted in **Fig. 3** from an actual dataset, to further illustrate the distribution of the nodes' staying times. The distribution shows that student nodes primarily remain in dormitories throughout a certain period of the day, which approximately obeys a power law distribution rather than a classical exponential distribution [23]. Consequently, we use the semi-Markov model to model the nodes' movements instead of the non-continuous-time Markov model. The Markov renewal process is a two-dimensional (state and time) random process, whereas the semi-Markov process is a one-dimensional random process produced by the Markov process. In the continuous-time Markov process, the staying time of the nodes in each state obeys an exponential distribution with the property of memorylessness, so that any moment can be an updated point. In other words, the Markov property exists at every time point. However, in the semi-Markov process, the staying time of each state can be generally distributed, and therefore, except for the state-switching moment, not all moments are updated points; only those points that are updated have the Markov property.

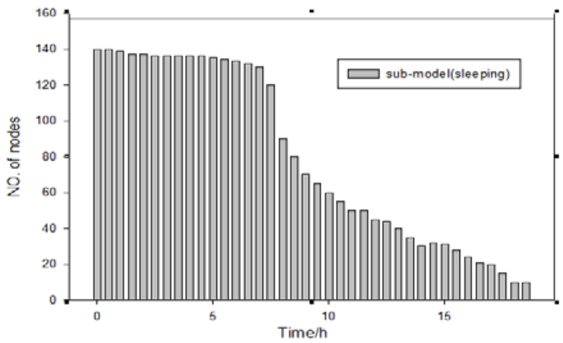


Fig. 3. Power law distribution

Assume that $\{T_n, X_n: n \geq 0\}$, where T_n represents the time of the n-th transition and X_n represents the spatial state in the opportunities network, $S = \{1, 2, 3, \ldots, J\}$, and J is the maximum number of communities. Further, assume that the probability of transition from state X_n to X_{n+1} is not related to previous state X_{n-1}; in other words, the node transition is memoryless in every state. Then, the random process X_n is a standard Markov chain.

The associated homogeneous semi-Markov kernel Q is defined by Eq. (1) [15]:

$$\begin{aligned} Q_{ij}(t) &= \mathrm{P}[\mathrm{X}_{n+1} = \mathrm{j}, \mathrm{T}_{n+1} - \mathrm{T}_n \leq \mathrm{t} \,|\, \mathrm{X}_n = \mathrm{i}\,] \\ &= \mathrm{p}_{ij}\mathrm{H}_{ij}(t), \mathrm{i}, \mathrm{j} \in \mathrm{S} \end{aligned} \tag{1}$$

where p_{ij} is the transition probability from state i to state j, $P = [p_{ij}]$ is the transition probability matrix of the embedded Markov chain, and H_{ij} is the staying time distribution of the waiting time when it switches from sate i to state j:

$$H_{ij}(t) = \mathrm{P}[\mathrm{T}_{n+1} - \mathrm{T}_n \le t \mid \mathrm{X}_{n+1} = j, \mathrm{X}_n = i] \quad (2)$$

Consequently, we can give the definition

$$D_i(t) = \mathrm{P}[\mathrm{T}_{n+1} - \mathrm{T}_n \le t \mid \mathrm{X}_n = i] \quad (3)$$

as the probability distribution of the staying time in state *i* in a time *t*, then

$$D_i(t) = \sum_{j=1}^{J} \mathrm{Q}_{ij}(t) \quad . \quad (4)$$

Assuming that time-homogeneous semi-Markov processes are defined as $X = (X_t, t \ge 0)$, the switching probabilities can be defined as in Eq. (5):

$$\begin{aligned} \phi_{ij}(t) &= \mathrm{P}[\mathrm{X}_t = j \mid \mathrm{X}_0 = i] \\ &= (1 - \mathrm{D}_i(t))\delta_{ij} + \sum_{l=1}^{J} \int_0^t \phi_{lj}(t-\tau)\, dQ_{il}(\tau) \\ &= (1 - \mathrm{D}_i(t))\delta_{ij} + \sum_{l=1}^{J} \int_0^t \dot{Q}_{il}(\tau)\phi_{lj}(t-\tau)\, d\tau \end{aligned} \quad (5)$$

where $\delta_{ij} = \begin{cases} 0, & \text{for } i \ne j \\ 1, & \text{for } i = j \end{cases}$.

3.2.2 Steady-state analysis model

In this subsection, we address the steady-state properties of the campus mobility model. Before we can obtain the steady-state probability distribution $[\phi_i^k]$ of a node, we first need to calculate two parameter matrices: transition probability matrix P^k and staying time probability distribution matrix $D_i^k(t)$.

As stated above, a node may stay in a community or move to other communities with a corresponding probability. We divide the activities into three periods of time, specifically, $T = \{T1, T2, T3\}$, where *T1* represents the time spent sleeping, *T2* represents the time spent in a classroom, and *T3* denotes the time spent on outgoing activities. State switching occurs when a node reaches the end time of any of these periods. **Fig. 4** shows the state switching of the proposed model with corresponding probabilities, and **Fig. 5** gives a detailed flowchart for the switching process among the sub-models. The switching process imitates the true daily life condition of the students with social bonds. The probabilities of all the activities are calculated via the semi-Markov chain switching probability. The choice of the means of transportation is based on the type of students—i.e., whether introverted or extroverted.

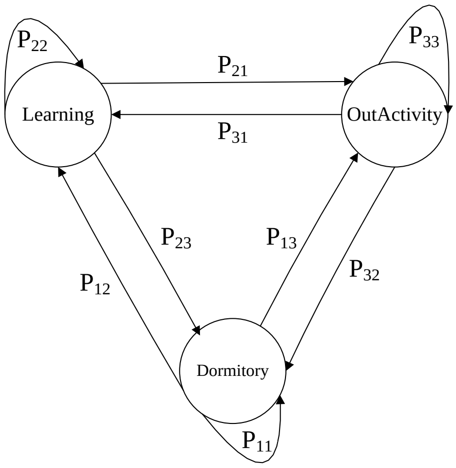


Fig. 4. Moving state transition probability of node k in the Markov model

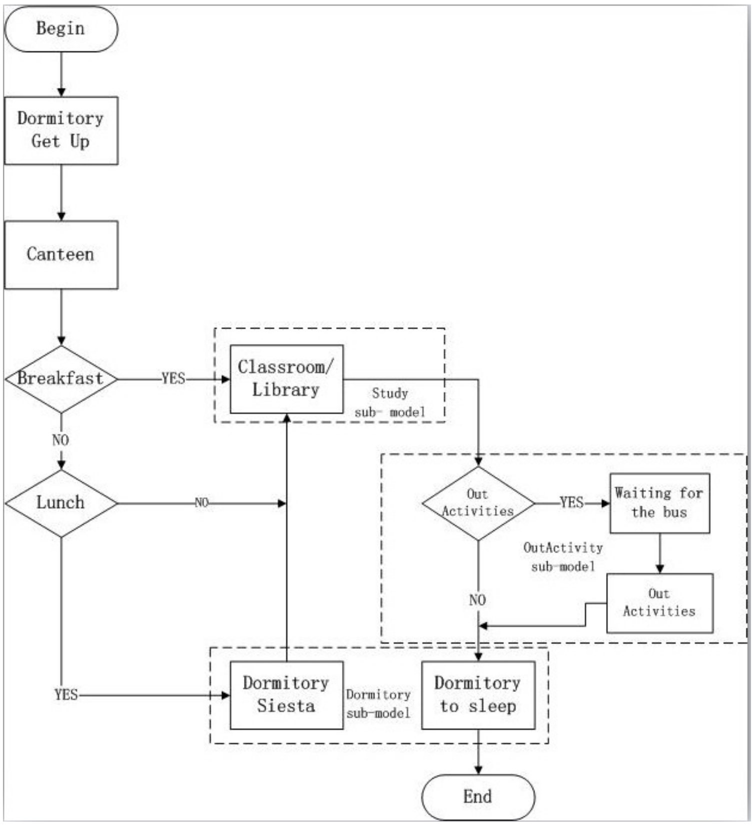


Fig. 5. Campus community model flowchart

If we assume that the Markov chain transition probability matrix of node *k* is represented as P_{ij}^{k} , then

$$\mathrm{P}_{ij}^{k} = \begin{bmatrix} \mathrm{p}_{11}^{k} & \mathrm{p}_{12}^{k} & \mathrm{p}_{13}^{k} \\ \mathrm{p}_{21}^{k} & \mathrm{p}_{22}^{k} & \mathrm{p}_{23}^{k} \\ \mathrm{p}_{31}^{k} & \mathrm{p}_{32}^{k} & \mathrm{p}_{33}^{k} \end{bmatrix} \tag{6}$$

Further, for any $i \neq j$, the switching probability for node *k* transferring from communi ty *i* to community *j* is calculated using Eq. (7):

$$\begin{cases} p_{ij}^{k} = \mathrm{P}[\mathrm{X}_{t+1}^{k} = \mathrm{j} \mid \mathrm{X}_{t+1}^{k} \neq \mathrm{i}, \mathrm{X}_{t}^{k} = \mathrm{i}] \\ \sum_{j \neq i} \mathrm{p}_{ij} = 1 \end{cases} \tag{7}$$

At this point, the staying time of node *k* is not considered during the calculation of transition probability matrix P^k . We assume that the length of time that node *k* spends in any state obeys a Gaussian distribution defined by Eq. (8):

$$D_i^k(t) = \left[\frac{1}{\sqrt{2\pi}\delta_i} \exp(-\frac{(x-\mu_i^k)^2}{2\delta_i^2}) \right], \mathrm{i} \in \mathrm{S} \tag{8}$$

The average staying time of $j \times 1$ dimensions of the vector is

$$\overline{D^k} = [\, \overline{\mathrm{d}_i^k} \,] = [\, \mu_i^k \,] \tag{9}$$

Consequently, we obtain the steady-state transition probability $\pi^k = [\pi_1^k, \pi_2^k, \pi_3^k, \ldots, \pi_J^k]$ of node *k* as given by Eq. (10):

$$\begin{cases} \pi_i^k = \pi^k P^k \\ \sum_{i=1}^{J} \pi_i^k = 1 \end{cases} \tag{10}$$

Therefore, the semi-Markov chain of node *k* among the three states in **Fig. 4** is

$$\pi_i^k = [\pi_1^k \ \ \pi_2^k \ \ \pi_3^k\,] \begin{bmatrix} \mathrm{p}_{11}^{k} & \mathrm{p}_{12}^{k} & \mathrm{p}_{13}^{k} \\ \mathrm{p}_{21}^{k} & \mathrm{p}_{22}^{k} & \mathrm{p}_{23}^{k} \\ \mathrm{p}_{31}^{k} & \mathrm{p}_{32}^{k} & \mathrm{p}_{33}^{k} \end{bmatrix}. \tag{11}$$

From Eq. (11), we find that

$$\begin{cases} \pi_1^k = \pi_1^k \, p_{11}^k + \pi_2^k \, p_{21}^k + \pi_3^k \, p_{31}^k \\ \pi_2^k = \pi_1^k \, p_{12}^k + \pi_2^k \, p_{22}^k + \pi_3^k \, p_{32}^k \\ \pi_3^k = \pi_1^k \, p_{13}^k + \pi_2^k \, p_{23}^k + \pi_3^k \, p_{33}^k \\ \pi_1^k + \pi_2^k + \pi_3^k = 1 \end{cases} \tag{12}$$

Thus, the steady-state probability distribution of nodes in an opportunistic network is given by

$$\phi_i^k = [\phi_i^k] = \frac{\overline{d_i^k} \, \pi_i^k}{\sum_{i=1}^{J} \overline{d_i^k} \, \pi_i^k} = \frac{\mu_i^k \pi_i^k}{\sum_{i=1}^{J} \mu_i^k \, \pi_i^k} \tag{13}$$

where $[\phi_i^k]$ is the steady-state probability distribution of node k in the community at any time. Finally, we obtain the steady-state probability distribution of node k in three communities at any time:

$$\begin{cases} \phi_1^k = \dfrac{\mu_1^k \, \pi_1^k}{\mu_1^k \, \pi_1^k + \mu_2^k \, \pi_2^k + \mu_3^k \, \pi_3^k} \\ \phi_2^k = \dfrac{\mu_2^k \, \pi_2^k}{\mu_1^k \, \pi_1^k + \mu_2^k \, \pi_2^k + \mu_3^k \, \pi_3^k} \\ \phi_3^k = \dfrac{\mu_3^k \, \pi_3^k}{\mu_1^k \, \pi_1^k + \mu_2^k \, \pi_2^k + \mu_3^k \, \pi_3^k} \end{cases} \tag{14}$$

This corresponds to the long-term distribution of node k in the network. Through analysis of the steady-state model of the mobile nodes in the network, we can estimate the distribution of student density in all communities.

4. Simulations and Performance Analysis

4.1 Simulation Assessment Parameter

In the wireless network design and simulation process, choosing the most appropriate assessment parameter is essential. Contact duration is the time interval in which two nodes are within radio range of each other, and inter-contact times define the frequency and the probability of being in contact with the recipient of a packet or a potential carrier in a given time period. These two parameters are commonly used to evaluate mobility models. A long contact duration implies that a large amount of data can be transferred (high throughput) and numerous inter-contact times imply more forwarding opportunities (short delays). Consequently, we used these parameters to evaluate the performance of the proposed model.

Definition: The complementary cumulative distribution function (CCDF) of a node’s contact duration and inter-contact times is given as follows:

Let t represent contact duration or inter-contact time, and N represent the number of t's in the datasets, where t_i (i = 1, 2, 3, …, N) is the ith contact duration or inter-contact time in the datasets. Thus, the sum of t being greater than the constant T is given by

$$num = \sum_{i=1}^{N} 1, \text{ where } t_i > T \tag{15}$$

Consequently, the CCDF of a node's contact duration and inter-contact times is given by Eq. (16):

$$P(T) = P(t > T) = \frac{num}{N}, \text{ where } T \geq 0 \quad , \tag{16}$$

where $P(T)$ is the probability that the value of the node's contact or inter-contact times is greater than a certain constant T in the datasets.

4.2 Experimental Results

In our experiments, we used the opportunistic network environment (ONE) [16] to simulate the proposed mobility model and an open source GIS program, called Open JUMP [17], to edit and convert the maps.

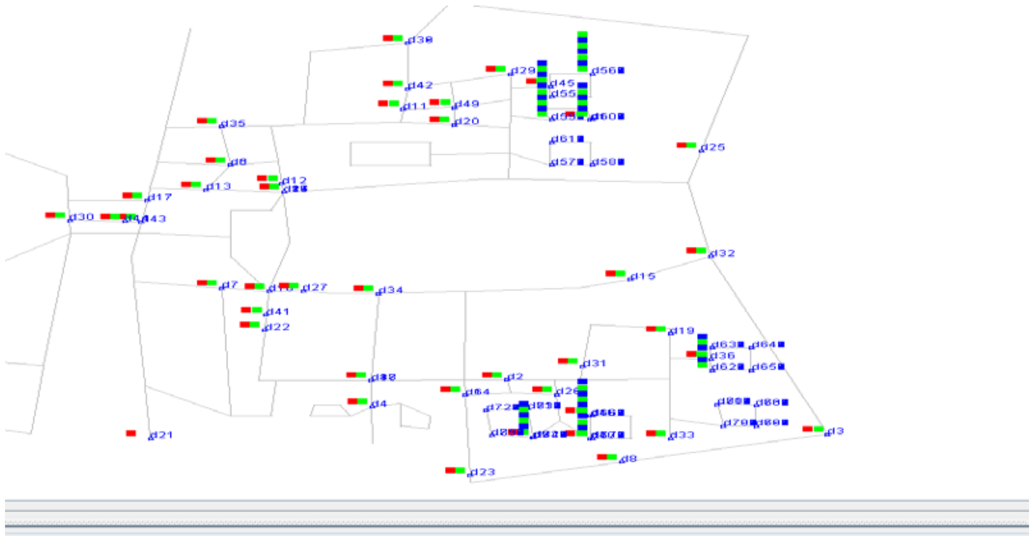
Table 1. Parameter settings

Parameter	Value
Simulation time (s)	43200
World size (m × m)	4500 × 3400
Communication method	Bluetooth
Node speed (m•s^{-1})	0.5–5
Transmission range (m)	10
Transmission rate (kbit•s^{-1})	250
Message size (kB)	500–1000
Message generation interval (s)	25–35
Class duration (s)	2400
Sleep duration (s)	14400
Number of nodes in a group	150
TTL_0: Time-to-live (s)	18000

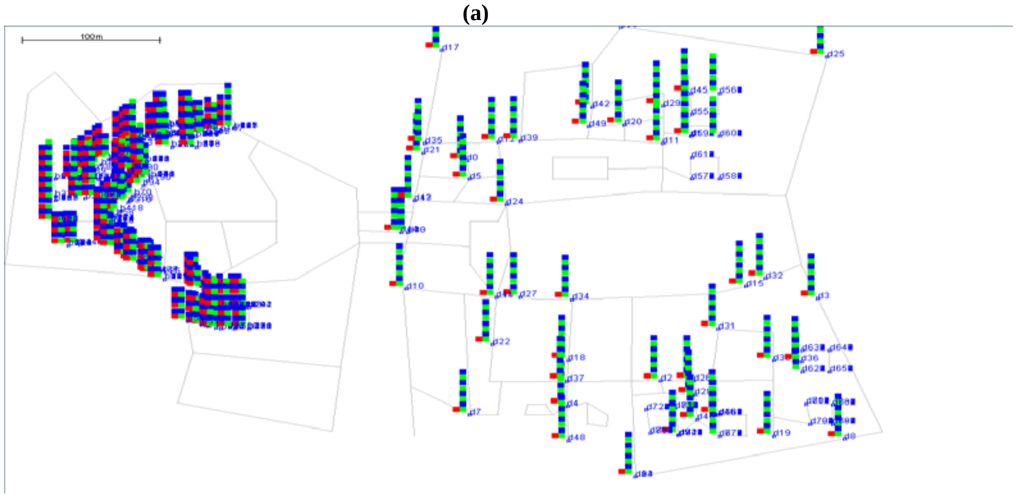
The basic variables used in the construction of the simulation environment were initialized in accordance with the proposed CBCNM (Section 3). We used the ONE simulation platform [16] for network analysis with epidemic routing as the routing protocol, and Open JUMP [17] to edit and convert the maps. The parameter settings used are displayed in **Table 1**.

The nodes of outgoing students have a greater chance than those of introverted students to choose outside activities. Among them, the state transition probability matrix of every group is initiated as $\begin{bmatrix} 0.1 & 0.8 & 0.1 \\ 0.8 & 0.1 & 0.1 \\ 0.1 & 0.8 & 0.1 \end{bmatrix}$.

Fig. 6 depicts the moving states of nodes for various time periods and probabilities in the simulation. The various student nodes in the sub-models are marked with different colors. A node is identified as an irregular node if it appears in an inappropriate area at a certain time; for example, any node that appears on a playground during the study period. As can be seen, most of the nodes have regular mobility, with only a few wandering into inappropriate sub-models throughout the day.



(a)



(b)

Fig. 6. States of the nodes in our simulation: (a) initialization, (b) nodes move from dorm to classroom with a large probability.

For comparison, we simulated an RWP on a simulation area of the same size. The moving speed and pause time were set in the ranges 1–5 m/s and 1–800 s, respectively, and were both uniformly distributed. We used two experimental datasets gathered by the CRAWDAD Project [18] in our evaluation, and compared the traces produced by Cambridge and Infocom 06. The performances of four mobility models—the proposed CBCNM, Cambridge, Infocom06, and RWP—are discussed and analyzed below.

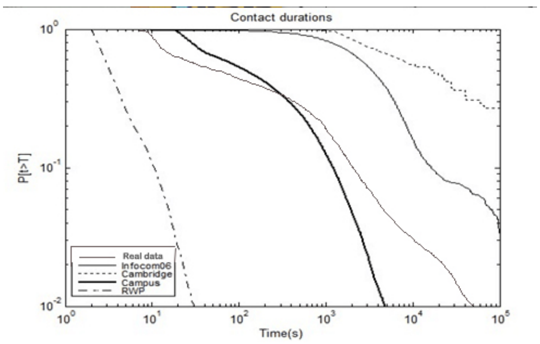


Fig. 7. Contact durations distribution

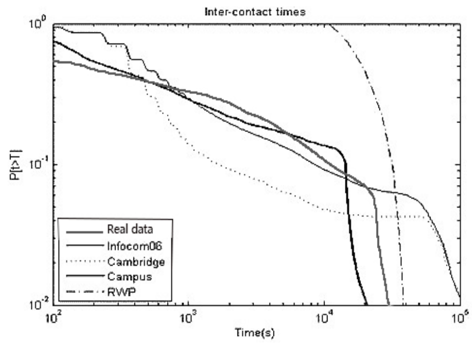


Fig. 8. Inter-contact times distribution

Fig. 7 shows the respective CCDF for Infocom 06, Cambridge, RWP, and Campus. As shown in the figure, contact duration approximately follows a power law distribution in log-log coordinates in the real dataset, with power law characteristics. The contact time between nodes in RWP is less than those in Campus, and there is no contact between 102 s and 104 s in RWP. This is because the RWP model is a synthesis model—node movement has a significant amount of randomness. As a result, RWP does not adequately depict social properties. In contrast, the Campus model is similar to the real dataset and adequately shows social attributes.

Fig. 8 depicts the CCDF of inter-contact times under the log-log coordinates in datasets. The traces of the campus model are approximately the same as the given real traces. The probability distributions of inter-contact times in RWP, Infocom 06, and Cambridge are more evenly distributed, while the interval of nodes encountered in these models are relatively long, especially in Infocom 06 and Cambridge, which is as much as 105 s, and results in fewer short contact intervals. Conversely, in the Campus model, there are shorter contact intervals and inter-contact times in the range 0–1000 s account for approximately 70%. For Infocom 06 and Cambridge inter-contact times account for approximately 90%.

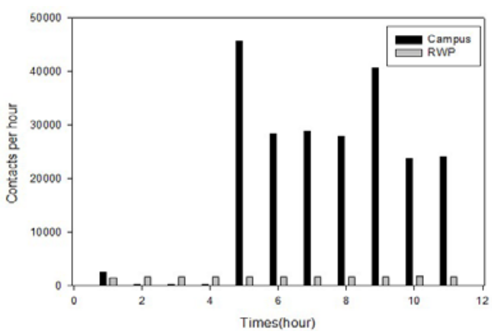


Fig. 9. Contacts per hour

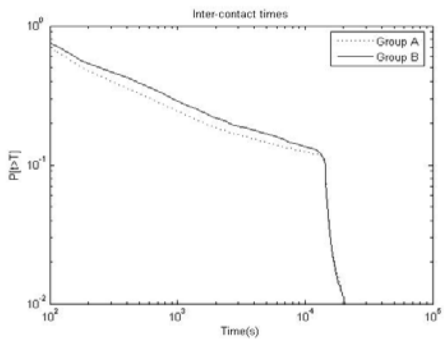


Fig. 10. Distribution of node inter-contact times for various state transition probability matrices

Fig. 9 shows the number of contacts per hour for all nodes. As can be seen in the figure, the number of contacts among all nodes in the Campus model varies at different time periods in every hour. During the first four hours, the number of contacts among nodes is small because the nodes are sleeping and so there are fewer opportunities for contact. Over the subsequent four hours, the number of contacts between nodes progressively increases, and eventually reaches a maximum of 5,000 contacts. This is because the nodes awake following a night of sleep, at which point state switching occurs, along with frequent contact between nodes. In addition, there is a rest period after each 40 minutes of lesson, which further helps to increase the number of contacts between nodes. Similarly, the number of contacts is also large for the last two hours. In contrast, the number of contacts remains the same in different time periods in the RWP model. The figure shows that the Campus model changes in accordance with the time period between the different nodes, which is consistent with the corresponding activities associated with the work schedules of students and teachers on an actual campus.

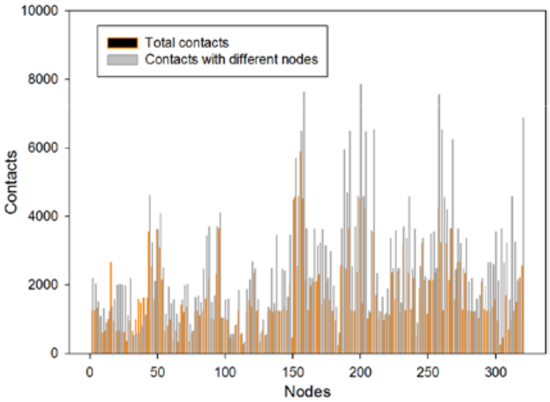


Fig. 11. Campus model

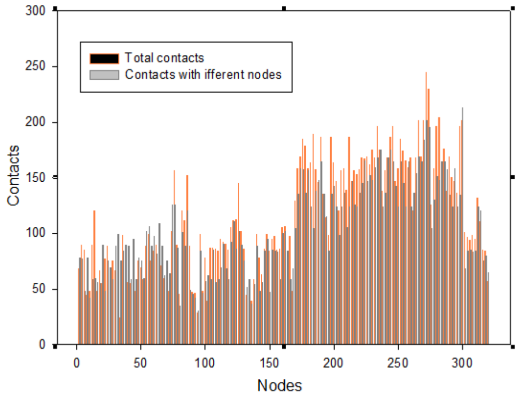


Fig. 12. RWP model

Figs. 11 and **12** show the total number of contacts for a single mobile node and the number for different nodes, respectively. As can be seen, in the RWP model, the mobile node is random such that the two kinds of numbers discussed above are relatively homogeneous and low as well. Conversely, in the Campus model, there are more contacts between the same nodes, which lead to a small number of contacts between different nodes. The result is consistent with the actual movements of students on campus, where three different communities exist, and nodes in the same community make contact with each other more frequently than those staying in different communities.

To show the difference more clearly, we can utilize another set of state transition probability matrices:

Let Group $A = \begin{bmatrix} 0 & 0.9 & 0.1 \\ 0.9 & 0 & 0.1 \\ 0.1 & 0.9 & 0 \end{bmatrix}$, and only consider the switching between different communities （Pii = 0） Group $B = \begin{bmatrix} 0.1 & 0.8 & 0.1 \\ 0.8 & 0.1 & 0.1 \\ 0.1 & 0.8 & 0.1 \end{bmatrix}$, as shown in **Fig. 9**.

Fig. 10 gives the CCDF of the distribution of node inter-contact times under various state transition probability matrixes. As shown in **Fig. 7**, the encounter intervals between nodes in group *B* are greater than those in group *A*. This is because the nodes in group *B* tend to move to more regions than those in group *A*. A node gets more opportunities to encounter others if it moves around one community because of the lower meet time interval.

As a result, the proposed Campus model can analyze the social characteristics of student nodes on an actual campus.

4.3 Routing Protocol Performance

In this section, we discuss the influence of campus community mobility models on the routing performance of classical routing algorithms in opportunistic networks. To evaluate the performance, we used several mobility models—the RWP model, the campus community model (Campus), and the SWIM model—then compared their performances by testing the data transmission performance with four kinds of routing: Epidemic [19], Spray and Wait [20], Prophet [21], and First Contact [22]. We used Delivered Ratio, Aborted Ratio, Latency Average, Overhead Ratio, and Average Buffer time as the main parameters in our evaluation.

From **Fig. 13**, it is clear that different mobility models influence the routing algorithms differently. The figure shows that the Campus model has the highest Delivered Ratio, especially for the Spray and Wait routing algorithm, with a value approximately 4.9 times that of RWP and 2.5 times that of SWIM. The Campus model also has the highest Delivered Ratio for the other three routing algorithms. Because RWP is a random mobility model in which nodes move without any pattern, its nodes have only a low possibility of meeting each other. By contrast, the Campus model reflects the actual behaviors of students and follows the three movement sub-models inside the community map; consequently, its nodes have a greater probability of meeting and transferring messages. Moreover, compared to the SWIM model, the Campus model has a higher Delivered Ratio, and has the better capability to transfer data. From these analyses we can conclude that the movement model has a significant impact on Delivered Ratio.

Fig. 14 shows the Aborted Ratio for each mobility model with the various routing algorithms. The figure shows that the Campus model is the best model as it has the lowest Aborted Ratio. With the Spray and Wait routing algorithm, the Aborted Ratio of the Campus model is close to 25.69% that of the SWIM and 24.52% that of the RWP models. With the First Contact routing algorithm, its Aborted Ratio is 18.14% that of the RWP and 19.52% that of the SWIM model. The Aborted Ratio results reflect broken links and nodes' out of communication range event occurrences. The lower the Aborted Ratio the greater is the probability that messages will reach the destination nodes. **Fig. 14** shows that the mobility models have a significant impact on the Aborted Ratio with various routing algorithms.

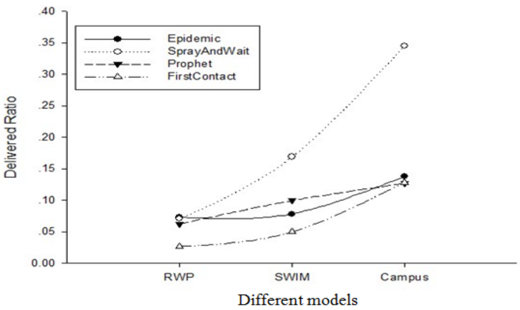


Fig. 13. Delivered Ratio

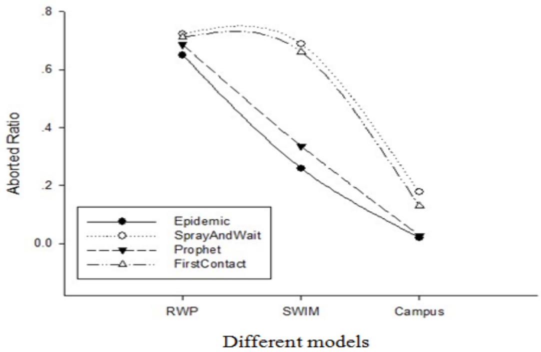


Fig. 14. Aborted Ratio

Figs. 15, 16, and **17** show the relationship between the mobility models and Buffer Time Average, Latency Average, and Overhead Ratio. As can be seen, the Campus model has a better network performance than the RWP and SWIM models. The Latency Average indicates the status of consumption of the room in the buffer. The shorter the Buffer Time Average, the more room is in the buffer and the greater the chance to transfer messages. **Fig. 15** shows that the Campus model has a shorter Buffer Time Average than the other two routing models, but is marginally higher with the Spray and Wait algorithm. Thus, it is clear that using the appropriate routing algorithm is important in an opportunistic network. **Fig. 16** shows that the mobility model influences the Latency Average under different routing algorithms. In this scenario, the Campus model value is lower than that of the RWP model. **Fig. 17** shows that the routing model also influences the routing overhead; however, the Prophet and First Contact routing algorithms are not significantly affected.

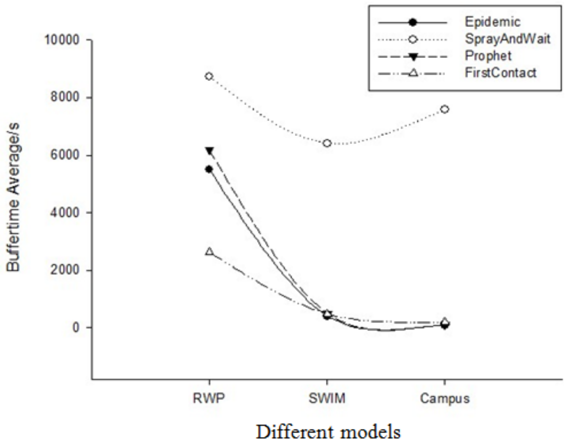


Fig. 15. Buffer Time Average

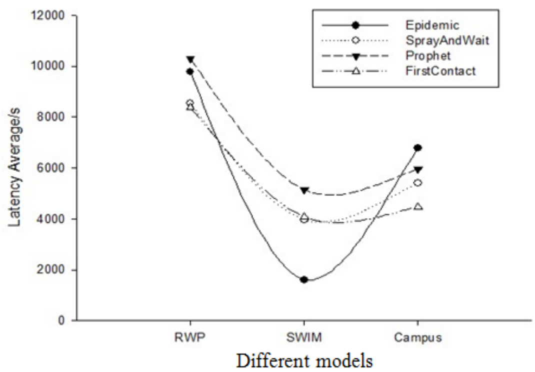


Fig. 16. Latency Average

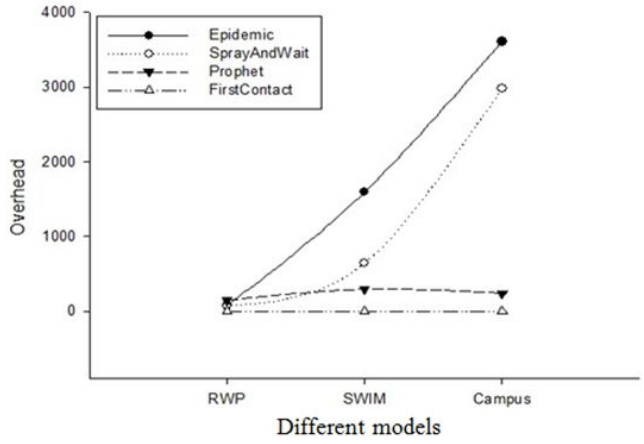


Fig. 17. Overhead Ratio

5 Conclusions

Mobility models are important in the research and analysis of routing protocols in opportunistic networks. In this paper, we proposed a campus community mobility model that simulates the daily life of students on a campus. The proposed model incorporates three different sub-models to capture the mobility characteristics in a specific campus environment, and model actual student mobility on campus. Consequently, it is able to reflect the unique aspects of campus life, whereas most conventional models cannot. We also showed that the proposed model is closer to the actual traces of data gathered from actual devices carried by students and have a better power law feature for the contact duration and inter-contact times of the nodes. Compared with the RWP model, the proposed mobility model better reflects the sociality of node mobility under the social environment of a campus. Finally, we also analyzed the influence of the campus-based community movement model on routing performance in opportunistic networks and showed that it results in better network performance than other models. We plan to extend the proposed model to other aspects of life, such as urban traffic, which can advance the opportunity for network research.

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References

[1] Pelusi L, Passarella A, Conti M, "Opportunistic networking: data forwarding in disconnected mobile ad hoc networks," *IEEE Communications Magazine*, 44(11): 134-141, 2006. Article (CrossRef Link).

[2] CHAINTREAU A, HUI P, CROWCROFT J, et al., "Impact of human mobility on the design of opportunistic forwarding algorithms[A]," in *Proc. of INFOCOM'06[C]*, 1-13, 2006. Article (CrossRef Link).

[3] Camp T, Boleng J, Davies V, “A survey of mobility models for ad hoc network research,” *Wireless Communications and Mobile Computing*, 2(5): 483-502, 2002. Article (CrossRef Link).
[4] Christian B, Hannes H, Hannes P C, “Stochastic Properties of the Random Waypoint Mobility Model,” *Wireless Networks*, 10(5): 555-567, 2004. Article (CrossRef Link).
[5] Mohd I, Zuriati A, “Performance Analysis of Random-Based Mobility Models in MANET Routing Protocol,” *European Journal of Scientific Research*, 32(4): 444-454, 2009. Article (CrossRef Link).
[6] Suvadip B, Parama B, “Improving network performance with affinity based mobility model in opportunistic network,” *Int J Wireless Mobile Networks* 4(2):189-202, 2012. Article (CrossRef Link).
[7] Hong X, Gerla M, Pei G, and Chiang C.C, “A group mobility model for ad hoc wireless networks,” in *Proc. of ACM Intern. Workshop on Modeling, Analysis, and Simulation of Wireless and Mobile Systems (MSWiM)*, August 1999. Article (CrossRef Link).
[8] Musolesi M, Mascolo C, “Designing mobility models based on social network theory,” *ACM SIGMOBILE Mobile Computing and Communications Review*, 11(3): 59-70, 2007. Article (CrossRef Link).
[9] Boldrini C, Passarella A, “HCMM: Modelling spatial and temporal properties of human mobility driven by users’ social relationships,” *Computer Communications*, 33(9):1056-1074, 2007. Article (CrossRef Link).
[10] Camp T, Boleng J, Davies V, “A survey of mobility models for ad hoc network research,” *Wireless Communications and Mobile Computing*, 2(5): 483-502, 2002. Article (CrossRef Link).
[11] Mei A, Stefa J, “SWIM: A Simple Model to Generate Small Mobile Worlds,” *INFOCOM 2009*, IEEE, 2009. Article (CrossRef Link).
[12] Kosta S, Mei A, Stefa J, “Small world in motion (SWIM): modeling communities in ad-hoc mobile networking,” *Sensor Mesh and Ad Hoc Communications and Networks (SECON), 2010 7th Annual IEEE Communications Society Conference on*, 2010. Article (CrossRef Link).
[13] Kosta S, Mei A, Stefa J, “Large-scale synthetic social mobile networks with swim,” *IEEE Transactions on Mobile Computing*, 13(1):116-129, 2014. Article (CrossRef Link).
[14] Injong R, Minsu S, Seongik H, et al., “On the levy-walk nature of human mobility,” *IEEE/ACM transactions on networking (TON)*, 19.3: 630-643, 2011. Article (CrossRef Link).
[15] Bolch G, “Queueing networks and markov chains: modeling and performance evaluation with computer science applications[M].” Article (CrossRef Link).
[16] Ari K, Teemu K, and Jorg O, “Simulating Mobility and DTNs with the ONE. Journal of Communications,” 5(2):1796-2021, 2010. Article (CrossRef Link).
[17] OPENJUMP-The free, java based and open source Geographic Information System for the World. Article (CrossRef Link).
[18] CRAWDAD, A Community Resource for Archiving Wireless Data At Dartmouth Haggle project. Article (CrossRef Link).
[19] Vahdat A, Becker D. Epidemic Routing for Partially-Connected Ad Hoc Networks. Technical Report CS-200006, Duke University, 2000. Article (CrossRef Link).
[20] Spyropoulos T, Psounis K, Raghavendra C S, “Spray and Wait: An Efficient Routing Scheme for Intermittently Connected Mobile Networks,” in *Proc. of SIGCOMM’05 Workshops*, 252-259, 2005. Article (CrossRef Link).
[21] Lindgren A, Doria A, Schelen O, “Probabilistic Routing in Intermittently Connected Networks,” *Service Assurance with Partial and Intermittent Resources*, 3126:239-254, 2004. Article (CrossRef Link).
[22] Jain S, Fall K, Patra R, “Routing in a Delay Tolerant Network,” *ACM SIGCOMM '04 ,Computer Communication*, 34(4): 145-158, 2004. Article (CrossRef Link).
[23] Pan H, Chaintreau A, Scott J, Gass R, Crowcroft J, Diot C, “Pocket switched networks and human mobility in conference environments[C],” in *Proc. of the 2005 ACM SIGCOMM workshop on Delay-tolerant networking*, 244-251, 2005. Article (CrossRef Link).

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