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Delay Management in Delay Tolerant Network

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SUMMARY

In delay tolerant networks (DTN), nodes explore various opportunities to connect and communicate with each other. A series of encounters of different nodes will create such opportunities and spread a message among many nodes and eventually deliver to the designated destination. We study one common DTN scenario where the message exchanges happen when nodes meet others at certain locations. In this situation, the success of message delivery and the quality of the delivery highly depend on the likeliness of nodes' encounters and time elapsed between encounters. We study the two important quality of service requirements: the probability of two nodes meeting each other (encounter probability) and the time it takes for two nodes to meet (encounter delay). The key considerations are how nodes pick its next locations (mobility patterns) and the features of the dwell time. In this paper, we will study several mobility patterns, including random movement, and activity agenda based movement. We also study an additional message delivery constraint, i.e., a message will be dropped if not delivered within a limited number of locations visited. We develop mathematical formulas using Markov Chain as a main tool. Our work is presented as an illustration through case studies. The methodology applies to mobility models alike and is extendable to real trace analysis. We present numerical results when closed form formulas cannot be acquired. Our results help the management of message delivery for delay tolerant networks, e.g., in selecting a proper time-to-live threshold for a message.

KEY WORDS: delay tolerant networks, encounter analysis, location-centric message delivery, encounter delay, encounter probability

1. INTRODUCTION

Nodes in mobile networks explore various opportunities to connect and communicate with other mobile nodes and fixed nodes. A typical form has been studied as delay tolerant networks (DTN), where communication nodes are mostly far away beyond their radio signal's reach, thus self-organized persistent connectivity does not exist. Nodes with messages to transmit rely on encountering other nodes during movement and then exchanging messages with each other [1]. *Encounter* could mean physical contact or coming within transmission range of each other. When nodes encounter, they are able to communicate, enabling many missions that are otherwise impossible because they are many

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hops away. A series of encounters of different nodes will spread the message among many nodes and eventually deliver it to the designated destination.

The importance of node encounter can be seen from the following examples. For large scale mobile networks, routing decisions can be made *solely* based on the history of encountering other nodes [2]. For this purpose, each node maintains a database to store the latest time and location of every other node it encountered. As a packet being forwarded towards its destination, each node is able to refine the estimation of the destination's location based on recently updated encounter histories from other nodes. In the area of security for mobile ad hoc networks, many schemes require *physical contacts* or direct links between nodes to setup keys between them or to establish trustness [3][4][5].

The norm in DTN is that nodes are not able to connect to each other most of the time. One common scenario is that nodes meet others at certain locations where they can exchange messages [6]. For example, in a remote rural area, people meet each other and exchange messages when they come to common places, e.g., post offices, drugstores. As another example, in the ZebraNet [7] that monitors the long term behaviors of zebra, water sources like lakes and rivers are the places that Zebras meet and wireless devices exchange messages. Recent work has analyzed WiFi network traces and discovered phenomena of the concentration of communications at locations (as well as motion patterns, flow patterns and social structures of mobile users)[8, 9, 10]. In these situations, the successfulness of message delivery and the quality of the deliver highly depend on the likeliness of nodes' encounters and time elapsed between encounters.

We are interested in the aforementioned *location-centric* delay tolerant network scenario. In this paper, we are motivated to study the above two properties of message delivery based on encounter, namely, the probability of message delivery based on two nodes meeting each other (*encounter probability*) and the latency of message delivery that depends on the time it takes for two nodes to meet (*encounter delay*). Note that study on encounter probability has been scattered in a few related work where DTN mobility models and routing schemes are proposed [11, 12, 13, 6, 14]. Our work makes contributions in that it is fully dedicated to study the encounter and message delivery issue for a set of mobility patterns and delivery constraint using Markov chain methods. Some of our results can be expressed in terms of a continuous time, rather then discrete events.

We adopt the mobility and communication model proposed early, i.e., nodes move among certain sites and they only communicate when they stay at those sites. Let there be n locations $1, 2, ..., n$. Nodes move from one location to another. Any node that moves to location i will stay there for a while. In the paper, we select a few mobility patterns for the analysis. The patterns differ in how a node picks its next location, typical, it could be random, or following an activity agenda. Further, we consider message delivery scenarios where delivery is not bounded by locations visited and delivery is constrained by the number of the locations being visited. Our analysis on message delivery properties are based on node movements among the locations. When nodes meet for the first time and messages are delivered, the analysis will not consider further movements, typically, our state transition goes to absorbing state.

We analyzed the node encounter problem through progressively complex scenarios, from not-so-realistic location independent and simultaneous movements to the more realistic time-variant and agenda-based movements, from the simple case that can be analyzed using direct probabilities to the complex case that can only be analyzed by continuous time Markov Chain. By taking a state as the current locations of two nodes, we obtain our results as a function of time. Some common trends can be seen following the analysis and numerical results. For example, two nodes eventually encounter each other given enough time - which implies that message eventually be delivered, it's only a matter of time; how fast they will encounter heavily depends on their initial positions and properties of all locations - whether a location has high attraction; whether nodes will stay long at this location; and even this location's relation with other locations - whether a node entering this location is more likely to move to another certain location? The methodology that we use here can extend to other possibly more complicated scenarios and mobility patterns. Following the direction of this work, we expect message delivery process will be more comprehensible given the encounter pattern of a Delay Tolerant Network is largely predictable by analysis. Our results help the management of message delivery for delay tolerant networks, e.g., in selecting a proper time-to-live threshold for a message. We present numerical results when closed form formulas cannot be acquired.

The rest of the paper is organized as follows. We first give a brief review on the related work in Section 2 and followed by an introduction to the system model in Section 3. We start with analyzing the case of constant dwelling time at the locations in Section 4, where discrete Markov chain is used. We then analyze encounter properties when the dwelling time is a variant in Section 5, where continuous time Markov chain is the tool for several mobility patterns. Section 6 concludes the paper.

2. RELATED WORK

Delay tolerant networking paradigm is suitable for many applications, where delay in message delivery is tolerable, for example, ZebraNet [7], remote rural villages [15], message ferry [16] and bus networks [17, 18]. Some researchers have studied efficient propagation of messages [19, 14, 20, 21, 2], while some others have studied how to explore mobility properties to achieve capacity and security [22, 5, 3, 23]. Our work relates to the former category, in that we analyze the probability and delay of message delivery. A few related work using on-the-fly data collection for calculating encounter probability to assist message propagation are given here. In probabilistic routing [14], the routing decision is made based on a metric called delivery predictability. *Delivery predictability* is established at each node for every other node indicating the predicated chance of this node delivering messages to the other node. Each time a node encounters another node, its delivery predictability to that node will be upgraded. The more frequent they encounter, the higher the delivery predictability. Similar encounter-based routing algorithm is also proposed in [2], where each node maintains a database of the time and location of its last encounter with every other node. Routing decision is made solely based on the encounter history. Several related analytical work are reviewed below.

In one type of the above research, a network scenario where contacts of nodes only appear at locations is studied and routing protocols are proposed [6, 8]. In Ghosh's work [6], each node moves among a list of places referred to as *hub*s. Each node has its own set of hubs. The authors used a semi-Markov chain to analyze the contact probability of two nodes at equilibrium and also the probability that one node meets another at a specific hub within time t. Closed form solution can be obtained for the first probability but not for the second. While this work focuses mainly on the routing protocol, the analytical part is rather sketchy. In contrast, our work includes more mobility patterns with more analytical details. In addition, we analyze the encounter probability when the number of locations visited is limited.

A more restricted two-hop relay network model, which was first proposed in [22], has been studied in Hanbali's work [13] [24][25]. In this model, to send a message to the destination, the source transmits a copy of the message to every neighbor it meets along its route. These neighbors are allowed to forward the copies to the destination only but no one else. Each copy of the message has a Time-To-Live (TTL). When TTL expires, this copy is destroyed. The paper analyzed *Meeting time* and *Inter-meeting time* of a given pair under the assumptions of the inter-meeting time of any two nodes following an exponential distribution with rate λ. Also suppose the TTL of any copy follows an exponential distribution with rate μ. This work differs from ours in several ways. First, the mobility model is different. Random walk or random direction model (which possesses the inter-meeting time property) are used where nodes move to any point in an area. Second, the research focus is on the number of message copies, not on the encounter behavior as we adopt here.

Paper [11] analyzed the hitting time (to a location) or meeting time (of two nodes) for random direction and random waypoint models. Closed forms of mean time were given. The authors also show that these results can be used to analyze the performance of mobility-assisted routing schemes. In paper [12], using wireless LAN traces, skewed location visit distributions and periodic visit behaviors are discovered and their impact on the hitting and meeting time are analyzed. While the analysis is based on discrete time unit in [12], our work uses continuous time analysis.

In summary, our work differs from the previous work in that we focus and provide more analytical results for mobility models and encounter delivery constraints. Our work contributes to the community with its analysis methodology and a better understanding on the properties of motion behaviors on message delivery in the delay tolerant networks.

3. SYSTEM MODEL

Our analysis of node encounter problem uses the following system model: There are n locations $1, 2, ..., n$. Nodes move from one location to another. Any node at location i will stay there for a time period. Messages could be delivered when two nodes encounter at a location. A message carrier may move across several locations while keeping a message before it meets a node and delivers the message. In this paper, we call each consecutive location visit as a "step". In our study, we focus on temporal properties that relate to the dwell time at those locations. Thus, we assume the dwell time at the locations are long so the transmit time from one location to the next can be omitted. We start our analysis with less realistic constant dwell time at the locations and move to more realistic variable dwell time at the locations. For the two cases, *discrete* Markov chain and *continuous* time Markov chain (CTMC) are used respectively (in Section 4 and Section 5). In the study of time-variant dwell time case, we also consider a message delivery constraint where the message will be invalid (so dropped) when the carrier has visited a fixed number of locations without delivery. This scenario could arise for a set of reasons, e.g., buffer full, message expires, or the duty of the message carrier.

Mobility patterns decide the way a node picking its next location. We study the following patterns: the selection of the next location is random, independent to the current location; the selection of the next location depends on the current location; and the selection of the next location follows an activity agenda, where a subset of all locations is available for random pick up for the next activity. In our examples, we always use two nodes, Alice as a message carrier and Bob as a recipient. When we use examples to illustrate the analysis results, we configure a network with three locations, see Fig. 1. In the figure, rectangles represent locations; triangle represents Alice and circle represents Bob. Three time instants are illustrated. From time t_0 at location 1, Alice moves to location 3 at time t_1, or to location 2 at time t_2. At location 2, massage exchange between Alice and Bob is possible.

Our main results show the encounter probability and encounter delay as functions of time. In practice, the dwell time of a location could be obtained through observations or consensus. The method used in this paper provides a way to generate the desired curves and select a Time-To-Live(TTL) threshold for the message at a desired delivery probability. A longer TTL allows a higher probability in general according to our results. Alternatively, our analysis also suggests a way to obtain the mean

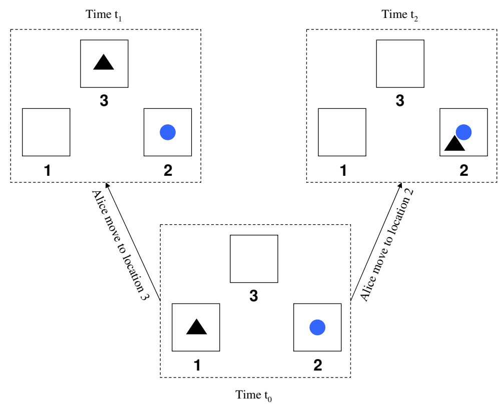


Figure 1. Node encounter scenario. Alice moves around, Bob stays at location 2.

delay time, which is the area covered by the curves of entering absorbing states. A TTL can also be selected as a multiplication of the mean delay. Because our analysis is based on discrete locations, the TTL should be updated only counting the actual time that a node stays at a location, ignoring the time on-road.

4. DISCRETE TIME ENCOUNTER ANALYSIS

Given nodes move among n locations, we study the case that the dwelling time at these locations are constant. Thus all nodes move simultaneously and we use the concept of *step* to describe the movements. A node picks its next location with a probability. The probability could be independent of or dependent on the current location. Different analysis methodology will be applied to the two cases. Our key problem is to obtain the encounter probability that the carrier (Alice) and the recipient (Bob) will meet within K steps (note that a node can visit the same location at different times) they visit.

4.1. Location independent movement

Assume for any node, the probability of visiting location i is $p_i, i = 1, 2, ...n$, no matter where he currently is. Notice that $\sum_{i=1}^{n} p_i = 1$. Then the probability that Alice encounters Bob in the first step can be simply computed as $s = \sum_{i=1}^{n} p_i^2$. The probability that they will encounter in the second step is $(1-s)s$ because of the location-independent movement. In general, the probability that they encounter in the i-th step follows a *geometric distribution* with parameter s. So the encounter probability of Alice meeting Bob within K steps is

$$\begin{aligned} Pr(\text{Alice encounters Bob}) &= s + (1-s)s + ... + (1-s)^{K-1}s \\ &= 1 - (1-s)^K \end{aligned} \tag{1}$$

Further, when the communication protocol extends to pass the original message to several carriers, say m Alice, and each carrier will deliver message to the recipient Bob, the probability of encountering

Bob is

$$\begin{aligned} Pr(\text{at least one Alice encounters Bob}) &= 1 - Pr(\text{no Alice encounters Bob}) \\ &= 1 - (1-s)^{mK} \end{aligned} \tag{2}$$

4.2. *Location dependent movement*

While the above case is too simplified, here we study a more realistic case, i.e, the choice of next location relates to the current one. Or say, the probability that a node visits next location is dependent on his current location. We formulate the problem using *discrete* Markov chain. We define a state (i, j) for the situation that Alice is at location i and Bob is at location j. We define an *absorbing state* y. It is the state when both nodes are at the same location, i.e, (i, i) for any location i. The time that Alice and Bob encounter each other is the time that the chain enters the absorbing state. We denote $\mathbf{p}_0$ to be the initial probability distribution of the Markov chain - a vector of probabilities for the chain starting at each state. Transition probability $q_{(i,j),(s,t)}$ is the probability that the chain is currently in the state (i, j) and will be in the state (s,t) at the next step. Thus the transition matrix $\mathbf{Q}$ can be denoted as

$$\begin{pmatrix} \mathbf{R} & \mathbf{Y} \\ \mathbf{0} & 1 \end{pmatrix}$$

where $\mathbf{R}$ represents the transitions between states that the two nodes are not in the same location; $\mathbf{Y}$ is a column vector representing the transitions into the absorbing state y. According to discrete Markov chain theory [26], the probability P_y^k that the two nodes encounter within the k-th transition of the chain (absorbed) can be computed by

$$P_y^k = \mathbf{p}_0 \mathbf{R}^{k-1} \mathbf{Y}, k \geq 1$$

Thus the encounter probability of Alice and Bob within K steps equals to

$$\begin{aligned} Pr(\text{Alice encounters Bob}) &= \sum_{k=1}^{K} \mathbf{p}_0 \mathbf{R}^{k-1} \mathbf{Y} \\ &= \mathbf{p}_0 (\mathbf{I} - \mathbf{R}^K)(\mathbf{I} - \mathbf{R})^{-1} \mathbf{Y} \end{aligned} \tag{3}$$

where $\mathbf{I}$ is the identity matrix. Let $\mathbf{A}$ be the probability of location transition from m to n, that is, for a node currently at location m, the probability of its next location being n is a_{mn}. Then we have $q_{(i,j),(s,t)} = a_{is} a_{jt}$ for non-absorbing states (i, j) and (s, t), due to the fact that Alice and Bob move independently (to each other). An element $q_{(i,j),y}$ of vector $\mathbf{Y}$ can be calculated simply as $1 - \sum_{\textit{all non-absorbing state } (s,t)} q_{(i,j),(s,t)}$.

4.3. *Examples*

Here we use two examples to illustrate above formulas. The network has three locations and two nodes, Alice and Bob. They move among these locations.

For the location independent case, we use the following three sets of visiting probabilities: $(p_1, p_2, p_3) = (0.7, 0.2, 0.1)$, $(p_1, p_2, p_3) = (0.2, 0.3, 0.5)$, and $(p_1, p_2, p_3) = (1/3, 1/3, 1/3)$. Typically, the first set shows a strong preference towards one location, and the third set is a pure uniform case. The encounter probabilities as functions of moving steps are shown in Fig. 2. The figure shows that encounter probabilities increase as moving steps increase. Strong preference on a location apparently has an impact and yields higher encounter probability, while the uniform location preference case has lower probability for encounter.

For the location dependent case, the probability of location transition from i to location j is given below.

$$\mathbf{A} = \begin{pmatrix} 0.1 & 0.4 & 0.5 \\ 0.3 & 0.2 & 0.5 \\ 0.6 & 0.2 & 0.2 \end{pmatrix}$$

For example, $A(2,3) = 0.5$ means that for a node currently at location 2, the probability of its next location at 3 is 0.5. Then we can compute:

$$\mathbf{R} = \begin{pmatrix} 0.02 & 0.1 & 0.15 & 0.12 & 0.2 & 0.05 \\ 0.12 & 0.04 & 0.06 & 0.06 & 0.1 & 0.3 \\ 0.24 & 0.08 & 0.02 & 0.02 & 0.1 & 0.3 \\ 0.12 & 0.2 & 0.05 & 0.02 & 0.1 & 0.15 \\ 0.06 & 0.1 & 0.3 & 0.12 & 0.04 & 0.06 \\ 0.02 & 0.1 & 0.3 & 0.24 & 0.08 & 0.02 \end{pmatrix} \quad \mathbf{Y} = \begin{pmatrix} 0.36 \\ 0.32 \\ 0.24 \\ 0.36 \\ 0.32 \\ 0.24 \end{pmatrix}$$

With three locations and two nodes, we have six possible initial states, such as $(1,1)$, $(1,2)$, etc. We choose three different sets of initial probability distribution $\mathbf{p}_0$: $(1\,0\,0\,0\,0\,0)$, $(0.2\,0.15\,0.15\,0.3\,0.1\,0.1)$, and $(1/6\,1/6\,1/6\,1/6\,1/6\,1/6)$. Again, the selections represent three cases: strongly uneven, random and pure uniform. The encounter probabilities as functions of moving steps are shown in Fig. 3. It shows that encounter probabilities increase as moving steps increase. But the initial probability distribution has less influence on encounter probability compared to the previous case, because the dependence on locations smoothed out the initial difference on location selections.

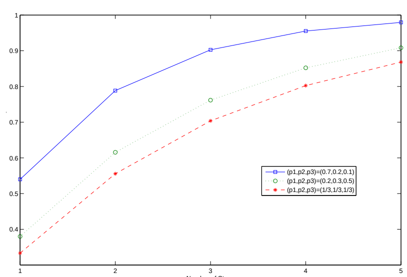


Figure 2. Encounter probabilities of discrete time movement: location independent movement.

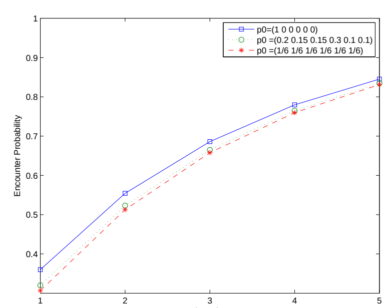


Figure 3. Encounter probabilities of discrete time movement: location dependent movement.

5. CONTINUOUS TIME ENCOUNTER ANALYSIS

We have analyzed the encounter probability in the scenario that the location dwelling time is constant. A more realistic scenario would be people staying at different places for different length of time, for example, 8 hours in office and 2 hours in restaurant; and at the same location, people can stay long or short in time. With this in mind, in this section we study message delivery properties for the scenario where the dwell time is a variable.

The problem can be analyzed using a *continuous* time Markov chain (CTMC) [26]. We assume dwell time to be exponential distribution with rate λ_i for location i. Our analysis focuses on obtaining the probability of message delivery within time t (*encounter probability*) and the mean delay before a message can be delivered (two nodes meet for the first time) (termed as *encounter delay*). Our analysis will study three cases: first, we study random movement, i.e., a node randomly picks next location with a probability; second, we add the message delivery constraint, i.e., the message delivery is bounded by a fixed number of locations (steps), otherwise, it is dropped; finally, we study the case where nodes pick locations from a subset according to a time schedule of activities.

5.1. Random movement

In random movement model, when a node leaves a location, it picks its next location randomly with a probability. We start with a simple two-node case and generalize to m nodes. In the analysis below, we assume equal probability for the ease of presentation. The same method can be used when probabilities are different.

Given Alice is at location i and Bob is at location j, the state of our Markov chain is represented as (i, j). Let random variable T_i represent the time a node stays at location i. Then the time the chain stays at state (i, j) is $T = \min\{T_i, T_j\}$. Apparently T follows exponential distribution with rate $\lambda_i + \lambda_j$. If Alice leaves first, she will enter any of the remaining $n - 1$ locations with equal probability. As a result the state transit from (i, j) to $(i_k, j), i_k \neq i$. Since Alice leaves location i with rate λ_i, the rate of entering state (i_k, j) is $\frac{1}{n-1}\lambda_i$. Likewise, if Bob leaves first, the state transforms into $(i, j_k), j_k \neq j$ with rate $\frac{1}{n-1}\lambda_j$. Finally, if Alice happens to move to the location where Bob is (and vice versa), they encounter each other and the Markov chain enters the absorbing state y. The rate of entering state y from state (i, j) is $\frac{1}{n-1}(\lambda_i + \lambda_j)$. Fig. 4 shows transitions leaving state (i, j). We can verify that the rate of leaving this state is $\lambda_i + \lambda_j$.

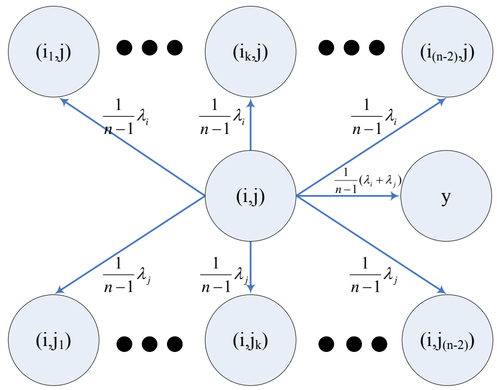
Let $v_{(i,j)}$ be the rate leaving state (i, j), $p_{(i,j),(s,t)}$ be the probability when leaving (i, j) it will next entering (s, t), y be the absorbing state when Alice and Bob are in the same location. Then we have

$$\begin{aligned}
v_{(i,j)} &= \lambda_i + \lambda_j \\
p_{(i,j),(i,k)} &= \frac{1}{n-1}\frac{\lambda_j}{\lambda_i + \lambda_j} \\
p_{(i,j),(k,j)} &= \frac{1}{n-1}\frac{\lambda_i}{\lambda_i + \lambda_j} \\
p_{(i,j),y} &= \frac{1}{n-1}
\end{aligned}$$

Let $p_{(s,t),(i,j)}(t)$ be the probability that the Markov chain, presently in state (s, t), will be in state (i, j) after an additional time t. Considering transforming from an arbitrary state (s, t) to another state (i, j), the Kolmogorov differential equations [26] are as follows:

$$p'_{(s,t),(i,j)}(t) = \sum_{k,k\neq i,j} \frac{1}{n-1}\lambda_k p_{(s,t),(i,k)}(t) + \sum_{k,k\neq i,j} \frac{1}{n-1}\lambda_k p_{(s,t),(k,j)}(t) - (\lambda_i + \lambda_j)p_{(s,t),(i,j)}(t)$$

Alice leaves location i. (n-2) possible transitions.
All with the same transition rate. $i_k \neq i$, (k=1,2,…,n-2).



Bob leaves location j. (n-2) possible transitions.
All with the same transition rate. $j_k \neq j$, (k=1, 2,…, n-2).

Figure 4. State transitions of random movement: from state (i, j) to other states. y is the absorbing state.

$$p'_{(s,t),y}(t) = \sum_{u,v,(u,v)\neq(s,t)} \frac{1}{n-1} p_{(s,t),(u,v)}(t)$$

Define *transition rate matrix* $\mathbf{Q}$ as

$$\begin{pmatrix} \mathbf{R} & \mathbf{Y} \\ \mathbf{0} & 0 \end{pmatrix}$$

where matrix $\mathbf{R}$ contains transition rates between transient states; column vector $\mathbf{Y} = -\mathbf{R}\mathbf{e}^T$ contains transition rates from transient states to the absorbing state y. Here $\mathbf{e}$ is a vector whose elements are all 1's.

Define *state probability* $p_s(t)$ as the probability the chain is at state s at time t. Then $p_y(t)$ is the probability the chain is at absorbing state at time t. Let $\mathbf{p}(t)$ be the *state probability vector* for transient states. $\mathbf{p}(0)$ is then the initial condition.

Then the Kolmogorov differential equation can be represented by the following matrix form:

$$[\mathbf{p}'(t)\ p'_y(t)] = [\mathbf{p}(t)\ p_y(t)]\mathbf{Q}$$

The solution is

$$\begin{aligned} \mathbf{p}(t) &= \mathbf{p}(0)exp\{\mathbf{R}t\} \\ p'_y(t) &= \mathbf{p}(0)exp\{\mathbf{R}t\}\mathbf{Y} \end{aligned}$$

where exp is the exponential function.

The probability that Alice encounters Bob after time t, starting from time 0, equals to

$$\begin{aligned} Pr\{\text{chain is at state } y \text{ at time } t\} &= p_y(t) = 1 - \mathbf{p}(t)\mathbf{e}^T \\ &= 1 - \mathbf{p}(0)exp\{\mathbf{R}t\}\mathbf{e}^T \end{aligned} \quad (4)$$

Let T_y be the random variable representing the time to reach the absorbing state (starting from time 0), i.e., the time to encounter. We have CDF

$$\begin{aligned} F_y(t) &= Pr\{T_y \leq t\} \\ &= Pr\{\text{chain is at state } y \text{ at time } t\} \\ &= 1 - \mathbf{p}(0) exp\{\mathbf{R}t\}\mathbf{e}^T \end{aligned} \tag{5}$$

Thus the average time to encounter each other for the first time $E[T_y]$ is:

$$E[T_y] = \int_0^{+\infty} t dF_y(t) = \mathbf{p}(0)\mathbf{R}^{-1}\mathbf{e}^T \tag{6}$$

GENERALIZATION Now we generalize the results obtained above to m nodes. Suppose there are m nodes (Alices), then the encounter probability is $1 - \prod_{i=1}^{m}(1 - p_i)$, where p_i is the probability Bob encountering Alice i after time t.

Next we consider the encounter delay. Let $T_{y1}, T_{y2}, ..., T_{ym}$ be random variables representing the time for the Bob to encounter Alices $1, 2, ..., m$ respectively. Apparently these random variables are independent to each other. Let their corresponding CDF be $F_{y1}(t), F_{y2}(t), ..., F_{ym}(t)$. Our first encounter time can thus be computed as $T_y = \min\{T_{y1}, T_{y2}, ..., T_{ym}\}$. So, its CDF is:

$$F_y(t) = 1 - (1 - F_{y1}(t))(1 - F_{y2}(t))...(1 - F_{ym}(t))$$

where individual $F_{yi}(t)$ is the same as the single Alice case that we analyzed above. If all m Alices are identical, we have $F_y(t) = 1 - (1 - F_{y1}(t))^m$. Given $F_y(t)$, we can compute $E[T_y]$ as before.

It should be pointed out that, in this paper, we do not consider the time moving between states because the moving time in general is much smaller than that of staying in any location. However, if the moving times are not negligible and have to be added in the model, we can simply add an additional state between any two states. For example, from state (i, j) to state (s, t), there would be a new state representing the moving time; the rate of entering this new state is same as the rate from state (i, j) to (s, t); the rate leaving this added state into state (s, t) is r, the value of which may depend on both states (i, j) and (s, t). Of course, we have to assume that moving time follows an exponential distribution.

EXAMPLE We illustrate the above analytical results through a simple example. Suppose there are 3 locations with rates $(\lambda_1, \lambda_2, \lambda_3) = (1, 2, 3)$. Here the location 3 is the most 'transient' location (nodes stay there for the shortest period of time). Initially Alice is at location 1 and Bob is at location 2. The complete state transition diagram is shown in Fig. 5. We use Maple to get numerical solutions. The encounter probability $p_y(t)$ is plotted in Fig. 6. It is expected that as time goes by, the two nodes will meet eventually. In the figure, we also plot the probability of the state $(1, 2)$: $p_{(1,2)}(t)$. Except that the two nodes stay at the state $(1, 2)$ at the initial time, the chance of staying at the state reduces as time passes by - they may enter other stats or they have encountered. Given any time t_0, we can find the encounter probability $p_y(t_0)$ from the curve of $p_y(t)$ in Fig. 6. According to our previous analysis, the CDF for T_y is the same as the curve of $p_y(t)$. Since $E[T_y] = \int_0^{+\infty} t dF_y(t)$, it is the area between this curve and the line $F_y(t) = 1$.

Other state probabilities $p_{(2,3)}(t), p_{(3,1)}(t), p_{(1,3)}(t), p_{(3,2)}(t)$ and $p_{(2,1)}(t)$ are plotted in Fig. 7. It shows that the curves have smaller probabilities compared to Fig. 6. This is largely because location

3 is the most 'transient' location in the system - so any states containing location 3 are short lived and thus lower in probabilities. The lowest probability is associated with the initial state $(1, 2)$. This is because that in order to reach state (2,1), the system has to go through at least one intermediate state. During the procedure, it is also possible that the system goes to absorbing state before it can reach this state. This figure also shows different values for different states. This differences come from the closeness of the states to the initial state $(1, 2)$. For example, the state $(1, 3)$ and the state $(3, 2)$ are more like to occur than the others if either Bob or Alice moves to location 3 respectively.

We also compare the encounter probability curves for different values of λ: a small set of values $(\lambda_1, \lambda_2, \lambda_3) = (0.5, 1.0, 1.5)$, a medium $(\lambda_1, \lambda_2, \lambda_3) = (1, 2, 3)$, and a large value set $(\lambda_1, \lambda_2, \lambda_3) = (2, 4, 6)$. The curves are shown in Fig. 8. Since a larger λ means a shorter dwell time at a location, which in turn means that nodes have higher mobility, it is not surprise that at any given time a system with larger λ values will always have higher encounter probability.

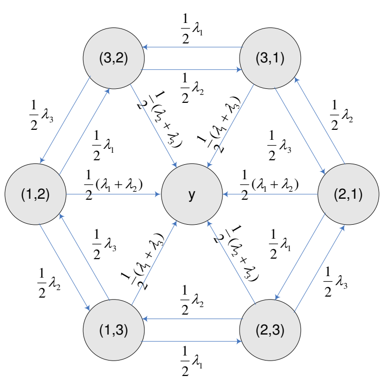


Figure 5. Complete state transitions of random movement: the three location example.

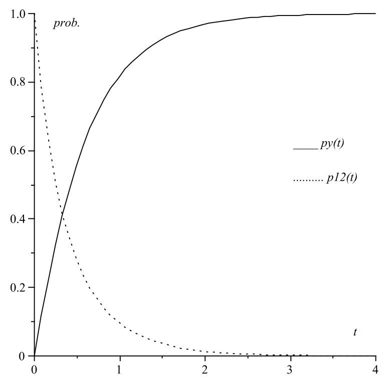


Figure 6. State probabilities of random movement: $p_y(t)$ and $p_{(1,2)}(t)$.

5.2. *Message delivery with step constraint*

Here we study the scenario that message delivery relates to the number of locations the message carrier Alice takes. Typically, the delivery will abort when a bound on the number of steps is reached. We do not apply a bound to Bob's movement assuming a recipient will always like to have a message. We still use the random mobility model. In using Markov chain to study this problem, we redefine the state to be (i, j, k), where (i, j) is the location of Alice and Bob respectively, k is the number of steps Alice has taken so far. The initial value of k is 0. Notice that a step means one visit of a location; it is not the "step" used in discrete Markov Chain - actually this problem has to be analyzed by continuous Markov chain. Similar Kolmogorov differential equations look the same as before, with the state now is (i, j, k).

We again use the 3-location case to illustrate our analysis. Suppose $\lambda_1 = 1, \lambda_2 = 2$ and $\lambda_3 = 3$. Also suppose initially Alice and Bob stay at locations 1 and 2 respectively; the maximum steps Alice can take is 2, i.e. $k \leq 2$. We will have 3 absorbing states: y_0, y_1 and y_2. We combine $(1, 1, 0)$, $(2, 2, 0)$ and $(3, 3, 0)$ into y_0 - encounter without Alice moving; $(1, 1, 1)$, $(2, 2, 1)$ and $(3, 3, 1)$ into y_1 - encounter after Alice takes 1 step; and $(1, 1, 2)$, $(2, 2, 2)$ and $(3, 3, 2)$ into y_2 - encounter after Alice takes 2 steps.

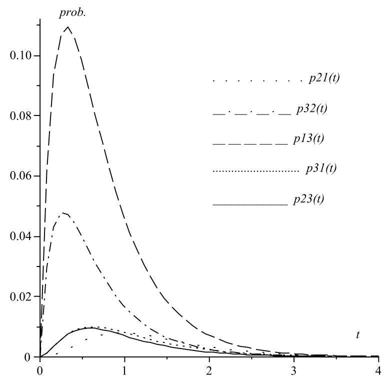


Figure 7. State probabilities of random movement: $p_{(2,3)}(t)$, $p_{(3,1)}(t)$, $p_{(1,3)}(t)$, $p_{(3,2)}(t)$ and $p_{(2,1)}(t)$.

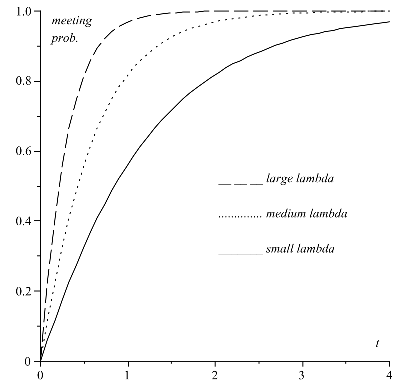


Figure 8. Encounter probabilities of random movement for three different sets of $(\lambda_1, \lambda_2, \lambda_3)$: small $(0.5, 1.0, 1.5)$, medium $(1, 2, 3)$, and large $(2, 4, 6)$.

For each absorbing state y_i, we can calculate the encounter probability and mean delay using the same method as in the previous subsection.

Numerical solutions are shown in Fig. 9. We have the following observations. Given t, the probability of encounter at 0, 1 or 2 steps are presented as the curves of $p_{y_0}(t)$,$p_{y_1}(t)$ and $p_{y_2}(t)$ respectively. In addition, we can obtain the mean time to encounter at 0, 1 or 2 steps as following. Let's consider the curve $p_{y_2}(t)$ in Fig. 9. At an arbitrary time t_i, $p_{y_2}(t_i)$ is the probability that Alice has taken 2 steps and has encountered Bob. The area between this curve and its asymptote is the mean time for Alice to encounter Bob after 2 steps. Notice that if Alice encounters Bob after 1 step, it will not take the 2nd step. The latter reason explains why $p_{y_0}(t)$ shows a higher probability than the other two, and why $p_{y_1}(t)$ shows a higher probability than $p_{y_2}(t)$.

5.3. *Agenda based movement*

Often, a node's movements are driven by his social activities. An agenda can be used to organize times and locations of the events. The agenda-based mobility model [27] captures such a reality. In this model, an agenda includes a series of activities that a node will participate for a day. Each activity includes a certain type of location and the time the activity begins. A node moves according to its agenda from one location to another to participate his activities. For one activity, a node may have many choices among several possible locations. For example, an agenda item may list the activity "lunch" at noon with several restaurant selections.

The agenda-based motion pattern reflects a real networking scenario for message delivery in DTN. We analyze it here. We keep the same assumption that the dwelling time at each location follows exponential distribution. The location of the next activity will be selected from a set of possible locations suitable for this activity with same probability (different probability case can be similarly handled). After finishing all activities on his agenda, a node repeats the agenda. We consider the case when Alice and Bob have the same series of activities on their agendas, however, the locations are not necessarily the same. The case of different agendas can be similarly analyzed.

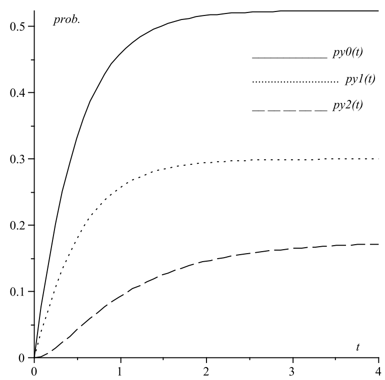


Figure 9. Encounter probabilities of random movement with step constraint: at 1, 2, or 3 steps.

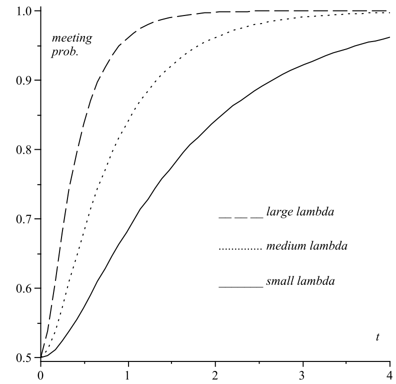


Figure 10. Encounter probabilities of agenda based movement for three different sets of $(\lambda_1, \lambda_2, \lambda_3)$: small $(0.5, 1.0, 1.5)$, medium $(1, 2, 3)$, and large $(2, 4, 6)$.

Let there be H activities in the agenda, noted as $A_0, A_1, ..., A_{H-1}$. For each activity A_i, there is a corresponding location set S_i. At the time of taking the activity A_i, one location will be selected from S_i. The size of S_i is denoted as $|S_i|$. We assume all H activities are different and thus all S_i's are disjoint, but they cover all n locations, that is, $\bigcup_{i=0}^{H-1} S_i = \{1, 2, ..., n\}$. Alice and Bob, starting from their respective initial locations (not in the n locations), enter S_0 to begin their agenda. After they finish all the activities in the agenda, they repeat agenda at locations in S_0.

A state is now defined as (i, j, k, l), where i is the location of Alice, j is the location of Bob, k is the number of steps Alice has taken so far, l is the number of steps Bob has taken so far. If $k < H - 1$ and Alice takes 1 step, entering location i', the state transforms to $(i', j, k + 1, l)$. Suppose it is equally possible to enter any state in S_{k+1}. Then the transition rate of this transformation is $\frac{1}{|S_{k+1}|}\lambda_i$. If $k = H - 1$, the system goes to $(i', j, 0, l)$. Notice that this indicates that when one finishes all activities, he/she goes back to activity A_0 and the number of steps is reset to 0. The corresponding transition rate is $\frac{1}{|S_0|}\lambda_i$. All states with $i = j$ and $k = l$ are combined into one absorbing state y which represents encounter. Encounter is only possible when Alice and Bob are in the same location set S_i which in turn happens only when they have taken the same number of steps. For a state to transform into absorbing state, it must satisfy $(|k - l| = 1) \vee (k = 0 \wedge l = H - 1) \vee (l = 0 \wedge k = H - 1)$. An example of state transitions starting from (i, j, k, l) is shown in Fig. 11. Other cases of state transitions can be similarly drawn. Since we have the state transition diagram, it is easy to set up Kolmogorov differential equations as before and obtain encounter probability $p_y(t)$ and the mean delay.

EXAMPLE We again use an example to show numerical results of the encounter probability $p_y(t)$. Suppose we have two activities A_0 and A_1 for Alice and Bob, and three locations with $S_0 = \{1, 2\}$ and $S_1 = \{3\}$. Notice that when Alice and Bob choose their locations for A_0, two locations in S_0 are available. Thus there is equal probability $(1/4)$ to be in the states of $(1, 2), (2, 1), (1, 1), (2, 2)$ respectively. For this example, Alice enters location 1 and Bob enters location 2. So initial condition is $\mathbf{p}(0) = (\frac{1}{4}\ 0\ 0\ \frac{1}{4}\ 0\ 0\ \frac{1}{2})$. We use three different sets of values for λ as before: a set of small

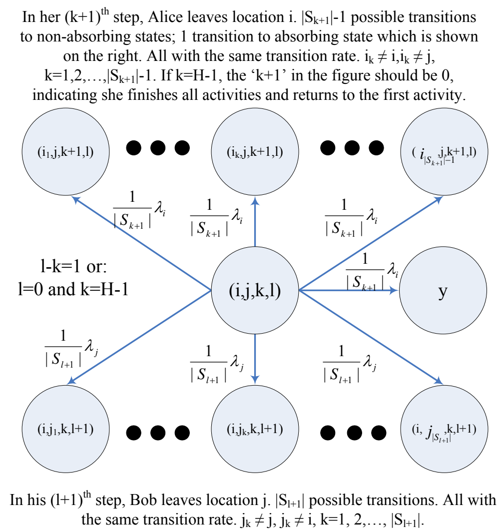


Figure 11. State transitions of agenda based movement: from state (i, j, k, l) to other states. y is the absorbing state.

values $(\lambda_1, \lambda_2, \lambda_3) = (0.5, 1.0, 1.5)$, a medium λs $(\lambda_1, \lambda_2, \lambda_3) = (1, 2, 3)$, and a set of large λ $(\lambda_1, \lambda_2, \lambda_3) = (2, 4, 6)$. A larger λ means a shorter staying at a location. The encounter probability curves are shown in Fig. 10. It shows that in a system with larger values of λ, nodes reach higher encounter probability more quickly.

6. CONCLUSION

In summary, we have presented a set of analysis on encounter probability and encounter delay for several mobility models for *location-centric* delay tolerant networks. The behavior of encounter is largely determined by the selection of the next location as depicted by the mobility models. In this regard, we have analyzed three mobility models, they are (1) random selection and independent from the current location, (2) random selection but depending on the current location, and (3) following an activity agenda. In addition to the location selection, dwelling time at these locations are also considered. They include constant and time-variant dwelling time. Further, we analyzed an additional constraint on message delivery, namely, the message will be dropped after the carrier has visited a fixed number of locations without delivery. To obtain the targeted encounter properties, we have used discrete Markov Chain and continuous time Markov Chain for constant dwelling time and time-variant dwell time, respectively. By taking a state as the current locations of two nodes, we obtain our results of encounter probability and encounter delay as a function of time. We illustrated our analytic work through easy-to-understand examples with numerical results. We expect such results help the management of message delivery for delay tolerant networks.

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