Deactivation-Controlled Epidemic Routing in Disruption Tolerant Networks with Multiple Sinks

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Abstract—To characterize the delivery performance of message dissemination in Disruption/Delay Tolerant Networks, various methods have been proposed. However, existing work shares a common simplification that the pairwise meeting rate between any two mobile nodes is exponentially distributed. In this paper, instead of relying on such assumption, we jointly consider the deactivation-rate over relay nodes and the number of sinks deployed in the network as the primary system parameters. Then, an ODE-based theoretical framework is proposed in a stochastic manner, which enables to describe how these two parameters affect the performance of a message delivery process using controlled epidemic routing. Via extensive experiments, the high accuracy of our analytical framework are verified.

I. INTRODUCTION

The development of sensor network technology has enabled the implementation of target detection and monitoring in a large scale environment, e.g., the habitat and vital signs monitoring for rare animals in wild animal sanctuaries [1]. Since the wireless sensors have the wireless communication capability, a Disruption/Delay Tolerant Network (DTN) can be constructed when these sensor-equipped animals roam in the sanctuary. In such network, instead of continuous connection between two mobile objects, there is only intermittent connection when they opportunistically get into the transmission range of each other during their movements.

In this paper, we are primarily interested in target monitoring problem by considering both moving source-target (red node) and other mobile objects, namely the mobile relays (blue nodes) and multiple sinks (grey nodes), in a DTN shown in Fig. 1. In such a network, one message $Msg$ is disseminated from the source target node to others periodically. Relay nodes help to forward copies of $Msg$. Once it is received by at least one sink node, it will be reported to the base station directly and immediately by the informed sink. Many practical applications in DTNs fall into such scenario, e.g., collection of the vital signs, habitat data and location information monitored by the sensor attached to the host animal in mobile sensor network, message dissemination in a battle field, and message forwarding in a pocket switched network in a campus.

Particularly, we are interested in the following two issues: 1) the evolution process of different types of mobile nodes during the message propagation, and 2) the relationship between delivery delay and the number of sinks deployed in the network. The evolution process means the constitution transformation of different types of mobile nodes as time goes by. Once we understand the evolution law of the message propagation, the deployment of mobile nodes can be controlled according to the theory. In the second issue, the delivery delay is defined as the duration from the generation instant of a message at the source target until its final reception instant by the first informed sink node. Without doubt low delivery delay is always preferred. The epidemic routing scheme has been proved as an efficient way to achieve the goal [2], [3] due to its greedy message forwarding manner, where a message is forwarded in a flooding style by fully exploring all communication opportunities such that it can be delivered to the sink as soon as possible.

Corresponding to the issues aforementioned, our objectives are: 1) establish the theoretical framework to describe the population evolution process of all types of mobile nodes; then 2) use the derived theoretical framework to find the connection between the number of sinks and delivery delay.

Based on an extensive review on related literature, we note that most current studies share a common simplification that the intermittent transmission opportunities can be described by an empirical exponential distribution of pairwise meeting interval between mobile objects [2], [4]–[7]. However, this assumption has the following limitations:

1) The pairwise inter-meeting time is often unknown in advance and its accurate value is hard to obtain.
2) Although it could be estimated under a certain mobility model, the analytical result is only applicable when the transmission range of a node is much smaller than the...
whole network region (Lemma 4 in [8]).

3) The analytical results can hardly be utilized by network operators for any optimization (e.g., minimizing delivery delay or energy consumption) because the inter-meeting time cannot be controlled directly.

This motivates us to investigate the delivery performance of epidemic routing in DTNs as a function of parameters that can be controlled directly. One such parameter is the deactivation-rate over the relay nodes. Because relay node may forward messages for many targets simultaneously. Excessive copies of message generated from different targets can occupy their buffer space too much [3] if without any control. It is obviously not beneficial to the propagation of messages. To tackle this problem, a reasonable method is to introduce a special parameter, i.e., the deactivation-rate [9], [10], which has an effect on the designated type of mobile nodes in network. We focus on deactivation over relay nodes in this paper. In fact, the deactivation-rate is a probability within (0, 1) that acts uniformly over all relays. In any time slot during a message’s propagation, the deactivated relay node becomes inactive. After that it will neither forward nor receive the message. Further, the message it has received shall be deleted to alleviate buffer occupancy, as well as to be ready to forward for other targets. Therefore, in order to control the message dissemination, it is significant to assign an appropriate deactivation-rate over relays.

Another parameter is the number of deployed sinks [10]–[13] in the network. It is believed that the more sinks are deployed, the lower delivery delay yields. However, it is a waste of investment if the network operator over deploys sinks to collect the target message. Therefore, it is crucial to understand the connection between the number of sinks and the delivery performance. To this end, we propose the conventional Ordinary Differential Equations (ODEs) based approach [2], [5], [6], [14] to construct the theoretical framework such that the delivery performance can be depicted accurately.

The major contributions of this paper are summarized as:

- To the best of our knowledge, we are the first to accurately analyze the delivery performance under general mobility model by treating deactivation-rate, the number of deployed sinks as the primary system parameters. Particularly, time-varying infectious and recovery rates are carefully derived to capture the population evolution process of all different types of mobile nodes over the network.
- The relationship between the number of sinks and the delivery delay is also investigated in a stochastic manner by applying the proposed theoretical framework.
- The correctness and high accuracy of our analysis are validated by extensive experiments.

The rest of the paper is organized as follows. Section II summaries related work. Section III introduces the system model. Section IV details our ODE-based stochastic analysis. The theoretical findings are verified by experiments in Section V. Finally, Section VI concludes this work.

II. RELATED WORK

Various epidemic routing protocols and analytical models have been proposed in [1]–[3], [5], [6], [14], [15]. We notice that they always assume the pairwise inter-meeting time between mobile nodes is known. For example, authors in [2], [6] assume that the inter-meeting time of any pair of nodes is an exponential random parameter with a given rate. As we have discussed, such empirical model is inaccurate and the rate is also difficult to be obtained in advance.

Under the classical assumption, much work has been conducted on the performance analysis of message dissemination in wireless mobile networks. Based on ODEs, Zhang et al. [2] developed a rigorous, unified framework to study the epidemic routing and its numerical variations. Lin et al. [6] introduce an analytical system to study the delivery performance of epidemic routing using network coding in opportunistic networks.

Our work differs from theirs, because we novelty propose a stochastic theoretical framework, which regards the deactivation-rate over relay nodes and the number of sinks as the significant system parameters that can be controlled directly, other than the empirical pairwise inter-meeting rate. The developed analytical framework is able to well depict the complicated message propagation process under the deactivation-controlled epidemic routing.

In other hand, to avoid high buffer occupancy level of relay nodes while using epidemic routing, Feng et al. [3] propose an encounter count quota, in which packets can only be delivered to a pre-defined threshold number of relay nodes. Yao et al. [16] use another controlled epidemic routing where each message is assigned a residence time when caching in a relay node. In this way, messages can be deleted automatically after the residence time expires such that both the buffer occupancy and caching energy consumption can be reduced. In contrast, we introduce another way to lower the high buffer occupancy, i.e., set a deactivation rate to each relay node corresponding to each target message.

III. SYSTEM MODEL

In this section, we introduce the system model used in this paper, which includes the basic network model, mobility model, and the controlled epidemic routing.

A. The Basic Network Model

We consider a DTN with a number of mobile nodes that are independently distributed within an square area. Without loss of generality, we suppose that all mobile nodes own the uniform transmission range, denoted by $r$. Two mobile nodes can directly communicate with each other if and only if their Euclidean distance is no larger than $r$. Furthermore, we also assume that the message can be completely forwarded during one transmitting opportunity.

B. Mobility Model

The Random Direction Mobility (RDM) [17] is considered as a general and widely adopted mobility model [1], [5], [8], [15], [18]. Initially, any mobile node chooses its direction
infect other susceptible nodes thereafter. An R
node can transform its state as a recovered node (K acts uniformly over all relay nodes, in any time slot, each
deactivation-rate is a probability within the range (0,1) that introduce a parameter R which can be illustrated by Fig. 2.
removed. Therefore, we can see that this type of controlled
occupancy, the message copy it has been received shall be with a probability R. A node (therefore this source node can be viewed as the first infectious
node (I-node). The message can be received by any sink node (K-node) and any relay node (Y-node). Hence, all the K-nodes and Y-nodes can be viewed as susceptible nodes. Once a susceptible node meets an I-node, it will receive a copy of the message, and become a new I-node, which will also be able to infect other susceptible nodes thereafter. An I-node always remains in infectious state. To receive the copy of the target message as soon as possible, we control all K-nodes keeping active. In other words, they can be always ready to receive the message. To the Y-nodes, to address the flooding problem because of excessive epidemic routing, we introduce a parameter ρ, which denotes the deactivation-rate over all relay nodes serving a specified target node. Since the deactivation-rate is a probability within the range (0,1) that acts uniformly over all relay nodes, in any time slot, each Y-node can transform its state as a recovered node (R-node) with a probability ρ. An R-node will neither forward nor receive the message any longer. Moreover, to relieve buffer occupancy, the message copy it has been received shall be removed. Therefore, we can see that this type of controlled epidemic routing is a variation of the famous SIR epidemic routing model [2], [14]. For short, we call it the IRYK model, which can be illustrated by Fig.2.

Suppose that there are one target node, N-1 relay nodes and K sink nodes in the network initially. Let I(t) (i(t)), R(t) (r(t)), Y(t) (y(t)) and K(t) (k(t)) denote the number (fraction) of infectious nodes, recovered nodes, relay nodes and the sink nodes at time t, respectively. Apparently, we have i(t) = \frac{I(t)}{N+K}, r(t) = \frac{R(t)}{N+K}, y(t) = \frac{Y(t)}{N+K} and k(t) = \frac{K(t)}{N+K}. Particularly, the equation i(t) + r(t) + y(t) + k(t) = 1, t ≥ 0 always holds in the message propagation process.

C. Controlled Epidemic Routing

In the focused DTN, the message generated in a source target node is disseminated to the entire network, and received by a sink at last. Initially, the target node creates a message and therefore this source node can be viewed as the first infectious node (I-node). The message can be received by any sink node (K-node) and any relay node (Y-node). Hence, all the K-nodes and Y-nodes can be viewed as susceptible nodes. Once a susceptible node meets an I-node, it will receive a copy of the message, and become a new I-node, which will also be able to infect other susceptible nodes thereafter. An I-node always remains in infectious state. To receive the copy of the target message as soon as possible, we control all K-nodes keeping active. In other words, they can be always ready to receive the message. To the Y-nodes, to address the flooding problem because of excessive epidemic routing, we introduce a parameter ρ, which denotes the deactivation-rate over all relay nodes serving a specified target node. Since the deactivation-rate is a probability within the range (0,1) that acts uniformly over all relay nodes, in any time slot, each Y-node can transform its state as a recovered node (R-node) with a probability ρ. An R-node will neither forward nor receive the message any longer. Moreover, to relieve buffer occupancy, the message copy it has been received shall be removed. Therefore, we can see that this type of controlled epidemic routing is a variation of the famous SIR epidemic routing model [2], [14]. For short, we call it the IRYK model, which can be illustrated by Fig.2.

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IV. Stochastic Analysis on the Message Dissemination Process

To monitor the target in DTNs, firstly we need to know the evolution principle that all types of mobile nodes obey. Then, it is important to make it clear how the focused parameters, namely the deactivation-rate over relay nodes and the number of sinks, affect the delivery delay experienced by the first sink. Once we address the two problems, the parameters of the network can be set appropriately according to the quality of service. In this section, we apply stochastic analysis method to investigate them respectively.

A. Evolution Process during Message Delivery

We set the system time when a message is generated at the source target node as $t = 0$ (i.e., $t=0$). Since then, the source target starts infecting other mobile nodes opportunistically during its travel. An infected mobile node is then able to infect other susceptible nodes. On the other hand, due to the introduction of deactivation-rate to Y-nodes, the population of relay node declines gradually. At time $t = 0$, since all mobile nodes are Y-nodes and K-nodes except that the source target node is the only I-node, we have the initial condition:

$$
\begin{align*}
I(0) &= 1, \\
R(0) &= 0, \\
Y(0) &= N - 1, \\
K(0) &= K.
\end{align*}
$$

Henceforth, whenever a Y-node or K-node moves into the transmission area of any I-node, it shall be infected. We call such transmission area as infectious area in the IRYK epidemic routing model. The transition rate of $I(t)$ therefore can be written as:

$$
\frac{dI(t)}{dt} = \frac{\rho_Y(t) \cdot S_{IA}}{dt} + \frac{\rho_K(t) \cdot S_{IA}}{dt}, \quad t \geq 0,
$$

where the first item in the right hand side equation denotes the increasing differential contribution from Y-nodes, while the second represents the increasing differential contribution from K-nodes. We define $\rho_Y(t)$ and $\rho_Y(t)$ as the density of Y-nodes and K-nodes, respectively, during the message propagation process. We further use $S_{IA}$ to denote the overall incremental infectious area of I-nodes. They can be derived as the follows.

$$
\rho_Y(t) = \frac{Y(t) \cdot \rho_0}{N + K}, \quad t \geq 0,
$$

$$
\rho_K(t) = \frac{K(t) \cdot \rho_0}{N + K}, \quad t \geq 0,
$$

$$
S_{IA} = I(t) \cdot d_S, \quad t \geq 0,
$$

where $d_S$ is the incremental infectious area of one I-node during the differential interval $[t, t+dt]$ as highlighted by the dark shadowed area in Fig. 3. Since this area is scanned by the mobile node with transmission diameter $2r$ with moving velocity $v$, it can be calculated as:

$$
d_S = 2r \cdot v \cdot dt.
$$
In summary, by taking (3), (4), (5) and (6) into (2), the infecting rate of $I$-nodes can be rewritten as:

$$I'(t) = 2rv\rho_0 \cdot I(t) \cdot [Y(t) + K(t)], \quad t \geq 0. \quad (7)$$

As we know, any $Y$-node shall only transform to $R$-node once they receive the message. Therefore, the transition rates of $Y$-nodes and $K$-nodes can be derived as follows.

$$\begin{align*}
\frac{dR(t)}{dt} &= \mu \cdot Y(t), \quad t \geq 0. \quad (8)
\end{align*}$$

From the infecting rate and recovering rate aforementioned, the transition rate of relay nodes includes the decreasing differential portions transforming to $I$-nodes and $R$-nodes, simultaneously. Since sink nodes always keep active, they shall only transform to $I$-nodes once they receive the message. Therefore, the transition rates of $Y$-nodes and $K$-nodes can be derived as follows.

$$\begin{align*}
\frac{dY(t)}{dt} &= -\rho_Y(t) \cdot S_{IA} - \mu \cdot Y(t), \\
\frac{dK(t)}{dt} &= -\rho_K(t) \cdot S_{IA}, \quad t \geq 0. \quad (9)
\end{align*}$$

B. Delivery delay

Due to the unexpected dynamics of DTNs, it is difficult to obtain the exact delivery delay of a message to mobile nodes. In this subsection, we shall derive the delivery delay distribution by a stochastic analysis.

**Definition IV.1.** Let $D$ denote the delivery delay experienced by the first informed sink node, and $F(t) = Pr(D \leq t)$ be the Cumulative Distribution Function (CDF) of delivery delays.

To obtain $F(t)$, we first need to calculate the probability that a $K$-node meets an $I$-node during a differential interval $[t, t + \Delta t]$.

**Lemma IV.2.** Let $N_I(t) = \rho_0 \cdot I(t) \cdot ds$ indicate the expected number of mobile nodes locating inside the overall incremental infectious areas, and $P_0$ denote the probability that a sink node meets an $I$-node during $[t, t + \Delta t]$. Then we have

$$P_0 = \frac{(K)}{N + K} \cdot \frac{(N_i(t))}{N + K}, \quad t \geq 0. \quad (10)$$

**Proof.** The probability of a $K$-node meets an $I$-node in $[t, t + \Delta t]$ equals the probability that a $K$-node locates in the incremental infectious area of any $I$-node during $[t, t + \Delta t]$. Then, $P_0$ is equal to the probability of selecting one mobile node from the network such that this node is within $N_I(t)$ as well as it is a $K$-node. Clearly, the number of all combinations that this selected mobile node is within $N_I(t)$ and is one $K$-node simultaneously equals to $\binom{K}{1} \cdot \binom{N_i(t)}{N + K}$. Furthermore, the number of cases that selecting one mobile node from the network is $\binom{N + K}{1}$. Therefore, the probability of a sink node meets an $I$-node in $\Delta t$ is $\frac{(K)}{N + K} \cdot \frac{(N_i(t))}{N + K}$.

Then secondly, we continue to derive the transition rate of $F(t)$ during the differential interval aforementioned.

**Lemma IV.3.** For any time instant $t \geq 0$, during a differential interval $\Delta t$, we have $F(t) = (2rv\rho_0 \cdot \frac{I(t) \cdot K}{N + K} \cdot \Delta t) \cdot (1 - F(t))$. 

**Proof.**

$$\Delta F(t) = F(t + \Delta t) - F(t) = Pr\{t \leq D < (t + \Delta t)\} = Pr\{a K\text{-node meets an } I\text{-node during } \Delta t\} \cdot Pr\{D \leq t\} = P_0 \cdot Pr\{D \leq t\} = \frac{(K)}{N + K} \cdot \frac{(N_i(t))}{N + K} \cdot (1 - F(t)) = (2rv\rho_0 \cdot \frac{I(t) \cdot K}{N + K} \cdot \Delta t) \cdot (1 - F(t)).$$

Finally, letting $\Delta t \to 0$, we can get the following differential equation on $F(t)$:

$$\frac{dF(t)}{dt} = (2rv\rho_0 \cdot \frac{I(t) \cdot K}{N + K}) \cdot (1 - F(t)), \quad t \geq 0. \quad (11)$$

Therefore, $F(t)$ can be solved in conjunction with the aforementioned ODEs (7), (8) and (9) with the initial condition $F(0) = 0$.

V. Evaluation

A. Basic Settings

We have developed a discrete-event simulator with C++ that strictly follows the system model described in Section III. The RDM mobility models and the controlled epidemic routing are implemented in the simulator to validate the accuracy of our analysis. In the simulations, mobile nodes are first randomly deployed sparsely in a $500m \times 500m$ square region. We set $N$ and $K$ to 200 and $\{10, 20, 50\}$, respectively, to evaluate the delivery performance on different network densities. After the initial deployment, nodes start moving according to RDM mobility model. The velocity $v$ is set as 10 m/s. The uniform transmission range of mobile nodes is fixed to 3 meters. For each simulation setting, 200 instances are conducted to obtain the average value. Besides the simulation results, we also build the corresponding ODEs and obtain the ODE-based analytical results applying the numerical ODE45 solving tool provided by Matlab.
B. The Accuracy of Propagation Process Analysis

To investigate the accuracy of our analysis on message propagation process, we firstly conduct a suite of simulation experiments under RDM mobility model with settings $\mu=0.01$ and $K \in \{10, 20, 50\}$. The evaluation results under variation settings of parameter $K$ are presented in Fig. 4, which depicts the evolution of $i(t)$, $r(t)$, $y(t)$ and $k(t)$. Obviously, our analysis shows high accuracy for all cases. There are several other observations we can find. In the first, with the same deactivation rate $\mu=0.01$, $y(t)$ shows as a deceasing function over system time in all three cases. Secondly, $i(t)$ converges faster and its converged peak value also becomes higher with the increasing $K$. Such a phenomenon can be attributed to that sink nodes will never be deactivated like relays, and with more sinks in the network, the transmitting opportunity becomes higher. As a result, the message is delivered faster and more relays and sinks become $I$-nodes. Simultaneously, fewer relays transform to $R$-nodes. Correspondingly, the peak value of $r(t)$ degenerates lower as the figures show.

Next, we study the delivery process under different $\mu$. Fig. 5 shows the evaluation results under the settings $K=20$, $\mu \in \{0.001, 0.005, 0.02\}$. From all these figures, clearly we see that $y(t)$ falls down sharper with the increasing $\mu$. 

Fig. 4. $i(t)$, $r(t)$, $y(t)$ and $k(t)$ under various values of $K$.

Fig. 5. $i(t)$, $r(t)$, $y(t)$ and $k(t)$ under various values of $\mu$. 
Correspondingly, more relays are deactivated to be $R$-nodes with a faster speed, and the converged peak value of $r(t)$ grows higher. This is because the transmitting opportunity decreases following the decreasing population of relays in the network. As a result, the message is delivered more slowly. Due to the same reason, the number of $I$-nodes in the network grows slower, too. Furthermore, more relays are deactivated to become $R$-nodes before being infected potentially. That is why the peak value of $r(t)$ becomes lower as Fig. 5 shows.

Overall, from both Fig. 4 and 5, we can always observe that the analysis on $i(t)$, $r(t)$, $y(t)$, and $k(t)$ matches the simulation results quite well. This validates the high accuracy of the proposed ODEs based analysis model for the single-message IRYK-like propagation process in DTNs.

C. The Accuracy of Delivery Delay Analysis

We also apply the same evaluation method to investigate the accuracy of the analysis on delivery delay experienced by the first sink. The CDF of delivery delays is also obtained through 200 instances for each simulation setting. Fig. 6 shows the CDF of analytical and simulation delivery delays under various values of $K \in \{10, 20, 50\}$ when $r = 3m/s$, $v = 10m/s$ and $N = 200$, respectively. It is observed that the expected delivery delays of sink becomes smaller while $K$ grows. For example in Fig. 6, there are 90% of the delivery delays occur at $t=50$ when $K=50$. However, these values drop to 50% and 30% when $K=20$ and 10, respectively. It is because the more sinks exist in the network, the higher transmitting opportunity becomes. In other words, the message can be delivered faster.

VI. CONCLUSION

In this paper, we investigate the message dissemination performance using controlled epidemic routing by introducing deactivation-rate over relay nodes in DTNs. The message propagation is modeled as a SIR-like process, which is able to characterize the evolution of different types of mobile nodes over the whole network. We apply our ODE-based stochastic analysis to describe such evolution by regarding the deactivation-rate over relay-nodes and the number of sinks as controllable system parameters. Furthermore, the relationship between the delivery delay and the number of sinks is also derived. Via extensive experiments, the correctness and high accuracy of our theoretical framework are verified.

ACKNOWLEDGMENT

This work is partly supported by Strategic Information and Communications R&D Promotion Programme (SCOPE No. 121802001).

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