Buffer Dimensioning of Delay-Tolerant Network Nodes - A Large Deviations Approach

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Abstract. Buffer dimensioning of nodes is essential to design a practical and efficient Delay-Tolerant Network (DTN). The existing literature on DTN assumes either infinite or finite (arbitrary) buffer size of the nodes in the system model; however, it does not quantify the buffer size. In this paper, we propose a large deviations framework to quantify the buffer size of DTN nodes moving according to Random WayPoint (RWP) mobility model and investigate the effect of buffer size in terms of its impact on the performance of underlying message forwarding protocol. Our extensive simulation results show that the performance of the proposed dimensioned buffer model is statistically equivalent to that of the infinite buffer model.

Keywords: Delay-tolerant network, buffer dimensioning, routing performance.

1 Introduction

Delay-Tolerant Networks (DTNs) are the networks that are attributed by the limitations (such as intermittent connectivity, asymmetric bandwidth, long variable delay, and high error rate) of contemporary networks [2]. DTNs are also referred by different names such as challenged networks, opportunistic networks, Intermittently Connected Mobile Networks (ICMNs), and Vehicular Ad-hoc NETworks (VANETs). The applications of DTN include vehicular networks, disaster response systems, and content distribution in Pocket Switched Networks (PSNs) [5].

In the context of buffer space, the existing literature on DTN assumes either infinite buffer size [10] or finite (arbitrary) buffer size [6], [14] of the nodes in its system model; however, to the best of our knowledge, buffer dimensioning of nodes in DTN is not studied much in detail. Further the store, carry, and forward paradigm [2] of the DTN architecture enables a node to carry the messages until it encounters the destination node or a potential relay node that has high probability of meeting the destination node. Because of this inherent nature of the program model, the nodes (that are bound by an arbitrary buffer size) can

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not afford to lose messages due to buffer overflow. Thus, a systematic way of quantifying the buffer size is paramount in designing a practical and efficient DTN.

In this paper, we propose an analytical framework based on Large Deviations Theory (LDT) [3] to quantify the buffer size of DTN nodes, and investigate the effect of buffer size in terms of its impact on the performance of underlying message forwarding protocol. The extensive simulation results validate the analytical results and show that the performance of the dimensioned buffer model is statistically equivalent to that of the infinite buffer model. In a nutshell, we bring the infinite buffer regime down to the reality platform (*i.e.*, dimensioned buffer model will show the same performance as delivered by the infinite buffer model) and also avoid the bottleneck (due to buffer overflow) as in the case of arbitrarily bound finite buffer models.

The organization of this paper is outlined as follows: We motivate our work in Sect. 2 by presenting real-world applications that are related to the system model under consideration. In Sect. 3, we focus on the DTN literature in the context of buffer sizing. Section 4 describes the system model in detail and lists out the notation used in the remainder of this paper. Sections 5 and 6 explain the analytical framework for buffer dimensioning of the DTN nodes and validate the results by extensive simulation in Sect. 7. Finally, we conclude the work and describe some future directions in Sect. 8.

2 Motivation

In this section, we present a couple of applications for which the node buffer capacity is to be dimensioned. We consider an animal monitoring application in a terrain over which the animals roam around for grazing. Every animal is attached with a sensor node (henceforth, called as *source node* in general). These nodes form a mobile DTN. Without loss of generality, the monitoring data could be any sensing data depending on the need. The sensed data is collected by mingling a subset of animals (henceforth, called as *destination nodes*) that belong to a specific herd equipped with the Internet infrastructure. The destination nodes will collect the data from the source node that comes within its coverage area. Later the destination nodes that go back to their herd would offload their collected data via Internet for further processing. The memory in these source nodes is considered to be one of the key resource in determining the cost and size of the sensor device. Hence, the goal of our work is to quantify (at the design phase) the buffer size in these source nodes.

In a similar way, this application is general enough to approximate vehicle monitoring applications in a campus, with the campus-shuttles acting as destination nodes and the corresponding shed providing the Internet backbone facility.

3 Related Work

Though buffer is considered as the vital resource in DTN modeling, there has been little research in the DTN literature, that focusses on the importance of the buffer sizing. The overhead in terms of buffer space required at each node is studied in [8]. The trade-off between delivery delay and buffer requirement is investigated across different static probabilistic forwarding protocols and the most buffer efficient scheme among them is found. In a similar way, the authors as a part of their work in [11] study the effect of buffer space on message delivery for the Spray-n-Wait routing protocol; however, these studies focus on the incidental impact of the arbitrarily bound buffer size on the routing performance and hence cannot be used in the design phase of a network, to quantify the size of the buffer.

The authors as a part of their work in [12] have computed the average value of per-node buffer occupancy by approximating the system model as $M/M/\infty$ queue; however, they did not quantify the buffer size in a complete way.

4 System Model

In this section, we present the system model that is used in analysis and simulation. The network has a total of $N + n_d$ nodes moving according to the Random WayPoint (RWP) mobility model [1]. The essence of the mobility pattern in the animal monitoring application as described in Sect. 2 is said to follow RWP mobility model. The authors in [9] map the group of zebras moving in a rectangular landscape composed of grazing areas and watering holes to the RWP mobility. The animal monitoring application under consideration also uses similar movement patterns with a traffic model on top of it.

All destination nodes n_d are considered to be the same, *i.e.,* delivering a message to any destination node is deemed as successfully delivered. This is valid because all the destination nodes will go back to the same herd to offload their data, hence no differences among them. Each of the N source nodes generates messages with the arrival rate following the Poisson distribution with parameter λ. The message forwarding scheme is the direct transmission scheme by which the source nodes deliver the messages directly to any one of the destination nodes they encounter. The notation used for this model is specified in Table 1.

The Inter-Meeting Time (IMT) between a pair of nodes is defined as the time gap between their two consecutive meetings, as illustrated in Fig. 1. According

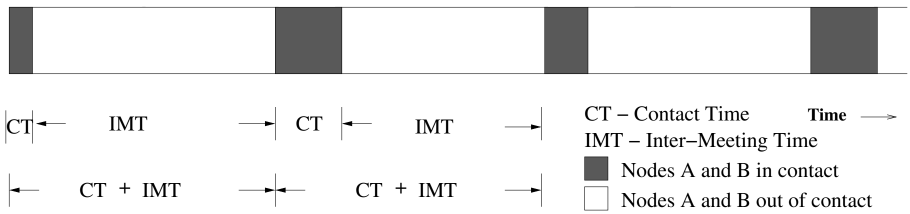

Fig. 1. CT and IMT patterns for a typical pair of nodes

Table 1. Notation used

Notation	**Meaning**
N	No. of source nodes
n_d	No. of destination nodes
$N + n_d$	Total no. of nodes
L	Packet size (KB)
W	Bandwidth ($Mbps$)
λ	Poisson message generation rate
A	Area of the square terrain
R	Transmission radius of the nodes
v	Constant velocity of the nodes
B	Buffer size (#packets)

to the work in [4], under RWP mobility model, the IMT between any pair of nodes is said to follow exponential distribution with parameter Γ given by

$$\Gamma = \frac{8\omega v R}{\pi A} \tag{1}$$

where ω is the RWP constant with value 1.3683, A is area of the terrain, v is constant velocity of the node, and R is transmission radius of the node. The Contact Time (CT) between two nodes is the period of time during which they are in continuous contact. The CT depends on the velocity v and transmission radius R of the nodes and the IMT in addition (to v and R) depends on the area of the terrain A as well. So the IMT dominates over CT and therefore IMT combined with CT can still be approximated to the exponential distribution with the same parameter Γ. This has been validated by simulating 20 nodes under RWP mobility model and the results in Table 2 show the average rate values (which are also the exponential distribution parameters) of IMT and IMT+CT for various number of destination nodes. The number of times a node meeting the destination node within time t is represented by a random variable $N(t)$. This random variable follows Poisson distribution. With slotted time, the probability that any node being in the range of the destination node in a time slot of length δt is given by

$$P[(N(t + \delta t) - N(t)) = 1] = e^{(-\Gamma \delta t)}(\Gamma \delta t) \equiv p\ . \tag{2}$$

5 Queueing Theory Approximation

Adopting a similar framework as in [13], we model each node as an M/M/1/B queue for the RWP mobility model. From Eq. 2, the probability that a source

Table 2. Average rate of IMT and IMT+CT for various n_d

No. of destn. nodes n_d	1	2	3
Analytical $\Gamma \times n_d$	0.00348	0.00696	0.01044
Empirical IMT	0.0034	0.00672	0.0099
Empirical IMT+CT	0.00327	0.0062	0.00882

node being in the range of any destination node (out of n_d of them) is given by $n_d p$. As a source node comes into contact with the destination node, its probability to transfer the message depends upon the other nodes that are within the range of the same destination node (due to the shared medium). Hence, the probability that a source node transfers a message to the destination node d in a time slot is given by

$$P_d = n_d p \times \sum_{k=0}^{N-1} \frac{1}{k+1} \times \alpha^k(d) \tag{3}$$

where $\alpha^k(d)$ is the probability that exactly k other nodes are in the destination node's vicinity, which is given by

$$\alpha^k(d) = \binom{N-1}{k} p^k (1-p)^{N-k-1} . \tag{4}$$

The number of time slots required to transfer a message successfully to the destination is represented by the random variable X. This random variable follows geometric distribution given by

$$P[X = n] = (1 - P_d)^{n-1} P_d . \tag{5}$$

If P_d is very small, this can be approximated to exponential distribution with the parameter μ given by

$$\mu = -\ln(1 - P_d) . \tag{6}$$

Since the data processing time is negligible as compared to the data transmission time (as physical mobility is involved), the rate μ is considered as service rate of the node. Figure 2 shows the exponential fit of the service rate for a typical node using Quantile-Quantile (Q-Q) plot. The linear behavior of the quantiles clearly shows that the service rate is following the exponential distribution.

6 Buffer Dimensioning Framework

In this section, we discuss the analytical framework for buffer dimensioning in DTN. In brief, the buffer size of each queue is studied in terms of buffer overflow probability by using the LDT framework.

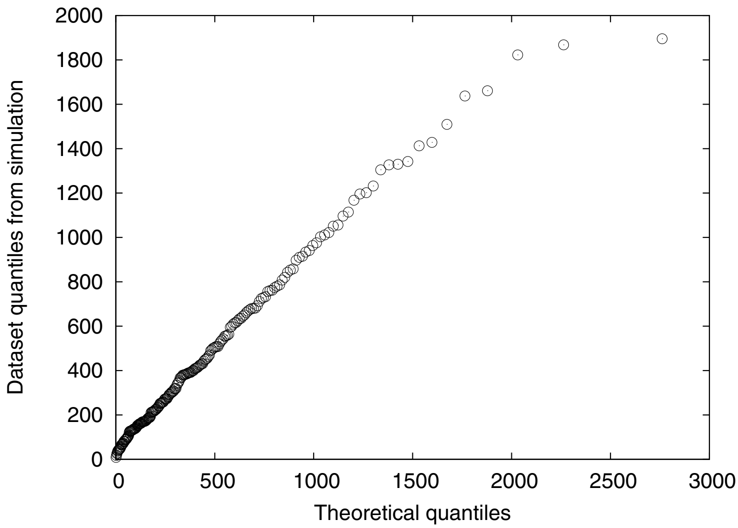

Fig. 2. Q-Q distribution fitting for the service rate of a typical source node

The total number of messages present in the queue Q at time t is equivalent to a recursive collection of number of messages in Q at time $t-1$ aggregated with the effective number of messages present at time t. This is represented by Lindley's recursion as follows:

$$Q_t = \Big[Q_{t-1} + A_t - C_t\Big]_0^B \tag{7}$$

where $[x]_0^B$ is $\max(0, \min(x, B))$, B is the maximum buffer capacity (in terms of number of messages), A_t is the number of messages that arrived in the interval $(t-1, t)$, and C_t is the number of messages served at time t. In our context, both A_t and C_t are Poisson processes. Let $Q_0^{-\infty}$ be the queue size at time 0, subject to the boundary condition that the queue was empty at $-\infty$. The workload process W_t is defined as

$$\begin{aligned} W_t = (A_{-1} - C_{-1}) + \cdots \\ + (A_{-t} - C_{-t}) \ . \end{aligned} \tag{8}$$

Applying the recursion to Eq. 7, $Q_0^{-\infty}$ can be represented as

$$Q_0^{-\infty} = \sup_{s \geq 0} W_s \ . \tag{9}$$

Assuming that the system had started at a finite time $-T$ with queue size being empty, Eq. 9 can be written as

$$Q = Q_0^{-T} = \max_{0 \leq s \leq T} W_s \ . \tag{10}$$

Now that the queue size has been described in the form of workload process, we focus on the steady (equilibrium) state of the queue size. This is the state of the queue size when the system is running for a sufficiently long time such that the initial state has no impact on the queue size. If the arrival and service processes are stationary (as in our case) and satisfy the stability conditions ($\lambda < \mu$), then the queue size Q is said to be in the steady state.

We need to study the tail of this steady-state queue length distribution. LDT [3], [7] is a theory of rare events applied to study the asymptotic behavior of the tails of probability distributions. The LDT on queue size [3] states that under stable condition ($\lambda < \mu$), the probability that the queue size is greater than some large value ($P[Q > q^*]$) decays exponentially as follows:

$$\lim_{l \to \infty} \frac{1}{l} \ln \mathbf{P}\left(\frac{Q}{l} > q^*\right) = -I(q^*) \tag{11}$$

such that the rate function $I(q^*)$ is given by

$$I(q) = q^* \times \theta^* \tag{12}$$

where the slope θ^* is $\max\{\theta : \Lambda(\theta) \leq 0\}$ and $\Lambda(\theta)$ is the cumulant (log moment) generating function of the queue process expressed in terms of arrival and service processes as follows:

$$\Lambda(\theta) = \Lambda_A(\theta) + \Lambda_C(-\theta) \tag{13}$$

such that $\Lambda_A(\theta) = \lambda(e^{\theta} - 1)$ and $\Lambda_C(-\theta) = \mu(e^{-\theta} - 1)$.

It is clear from Eq. 11 and Eq. 12 that under logarithmic scale the decay rate is linear as a straight line $\gamma = mx$, where $\gamma = \ln P(Q > q^*)$, slope $m = \theta^*$, and $x = q^*$.

The buffer loss probability exponent γ is considered as the decision parameter and the required buffer size q^* is computed from Eq. 11 as $e^{-\gamma} = e^{-I(q^*)}$. Therefore the buffer size q^* is computed by

$$q^* = \frac{\gamma}{\theta^*} \; . \tag{14}$$

7 Analytical and Simulation Results

In this section, we validate the analytical framework presented in the previous section and verify the statistical equivalence of the dimensioned buffer (q^* from Eq. 14) model with that of the infinite buffer model by studying the performance of routing protocol, using ns-2 simulator.

7.1 Performance Metrics Used

- Delivery ratio: The ratio of the number of messages delivered at the destination node to the total number of messages generated.
- Delivery delay: The delay incurred by sending the messages from the source node to the destination node.

Table 3. Simulation parameters

Parameter	**Value**
No. of source nodes (N)	20
No. of destination nodes (n_d)	1
Arrival rate (λ)	0.003
Mobility model	RWP
Terrain size	$500m \times 500m$
Transmission radius of the nodes (R)	$50m$
Velocity of the nodes (v)	$5m/sec$
Packet length (L)	$1KB$
Bandwidth (W)	$1Mbps$

– Message loss ratio: The ratio of the number of messages dropped by a source node (due to buffer overflow) to the total number of messages generated in that node (averaged across all source nodes).

7.2 Simulation Setup

In this section, we describe the simulation settings in detail. The mobility model is parameterized in such a way that $\Gamma = 0.00348$. The complete simulation settings are enlisted in Table 3. *TwoRayGround* is the propagation model under consideration with all nodes using 802.11 as the MAC protocol. All graphs are plotted with 95% confidence level.

7.3 Simulation Results

Figure 3 shows the Complementary Cumulative Distribution Function (CCDF) of the individual queues $P[Q > q]$ plotted in the logarithmic scale for various buffer sizes q. The CCDF is observed to follow a straight line decay with negative slope and is in line with the analytical slope θ^*. All queues eventually end by tailing off, since beyond some point in time there are no messages in the nodes. This is due to the fact that the rare probabilities can only be captured in a relatively large amount of time.

Figure 4 shows the simulation results for $n_d = 1$. The delivery ratio increases with an increase in buffer size. This is because an increase in buffer size reduces the percentage of message drops. The delivery delay also increases with an

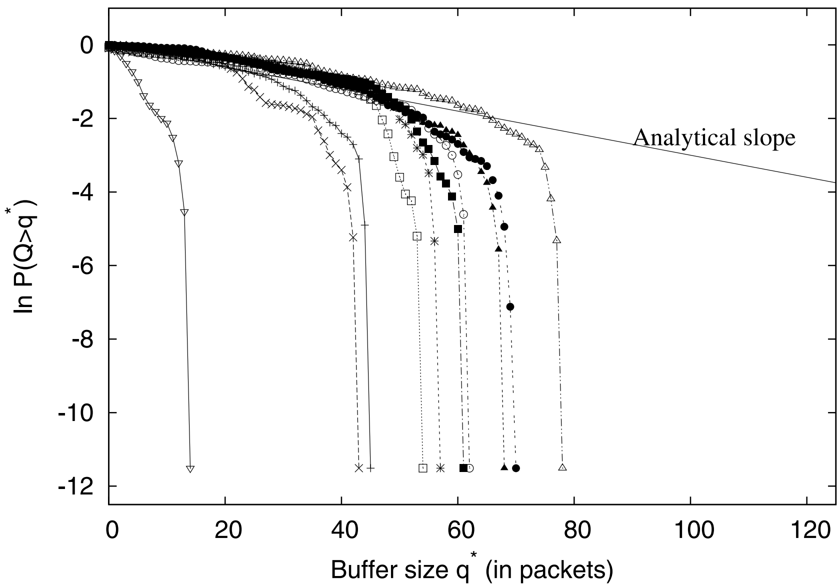

Fig. 3. Log CCDF vs buffer size for different source nodes

Table 4. Buffer size q^* at mean arrival rate 0.003 for various exponential loss probability exponent γ

n_d	θ^*	Buffer size q^*			
		$\gamma = -1$	$\gamma = -2$	$\gamma = -3$	$\gamma = -4$
1	0.03	33.34	66.67	100	133.34

increase in buffer size, since the number of messages that contribute to the delay increases with an increase in the buffer size.

The *saturation line* in Fig. 4 is drawn at the specific buffer size where the message loss ratio reaches zero. This is the buffer size at which the bottleneck (due to the buffer overflow) becomes negligible and the underlying primitive routing protocol does not inhibit the performance. It is clear from Table 4 and Fig. 4 that the dimensioned buffer size q^* at a reasonable value of the decision parameter γ (such that $P(Q > q^*)$ is close to 0 and this occurs at $\gamma < -4$) lies far ahead of the saturation point showing clearly that the system at this buffer size in the nodes would provide a performance statistically equivalent to the infinite buffer model.

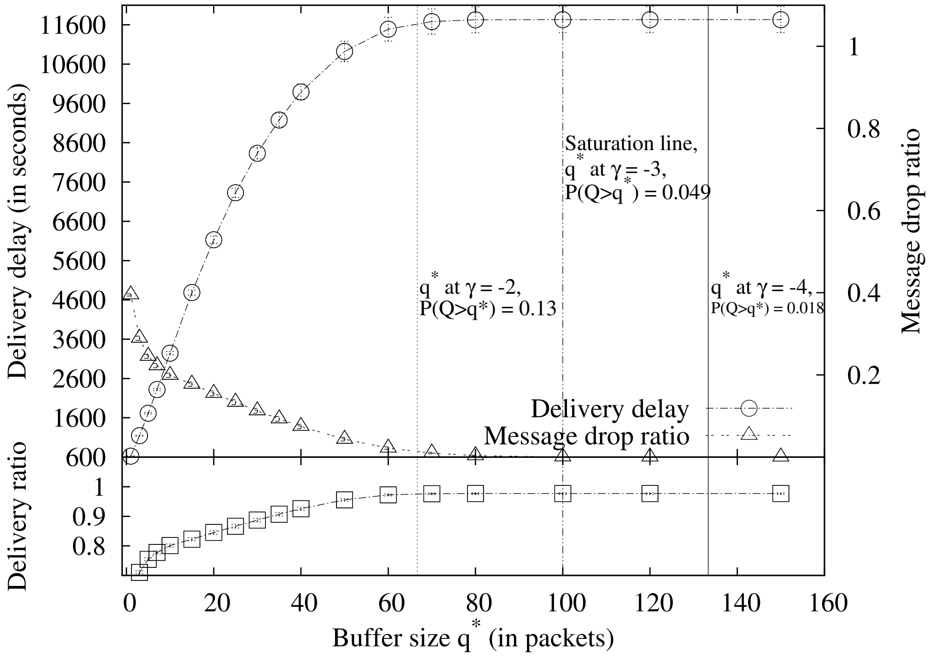

Fig. 4. Performance metrics vs buffer size

8 Conclusion and Future Work

In this paper, we proposed a large deviations framework to dimension the buffer size of the DTN nodes moving according to RWP mobility model and demonstrated the effectiveness of this dimensioned buffer model–in terms of the performance of the message forwarding protocol (average delivery delay and average delivery ratio)–by showing the statistical equivalence to that of the infinite buffer model. We plan to extend this work by investigating the buffer size for a family of generic DTN that involves instability regime as well.

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