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On throughput capacity of large-scale ad hoc networks with realistic buffer constraint

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Abstract The problem of determining the throughput capacity of an ad hoc network is addressed. Previous studies mainly focused on the infinite buffer scenario, however, in this paper we consider a large-scale ad hoc network with a scalable traffic model, where each node has a buffer of size B packets, and explore its corresponding per node throughput performance. We first model each node as a G/G/1/B queuing system which incorporates the important wireless interference and medium access contention. With the help of this queuing model, we then explore the properties of the throughput upper bound for all scheduling schemes. Based on these properties, we further develop an analytical approach to derive the expressions of per node throughput capacity for the concerned buffer-limited ad hoc network. The results show that the cumulative effect of packet loss due to the per hop buffer overflowing will degrade the throughput performance, and the degradation is inversely proportional to the buffer size. Finally, we provide the specific scheduling schemes which enable the per node throughput to approach its upper bound, under both symmetrical and unsymmetrical network topologies.

Keywords Capacity · Ad hoc networks · Buffer constraint · Queuing analysis · Network scheduling

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1 Introduction

The ad hoc network can be defined as a collection of nodes which communicate with each other without centralized infrastructure [1]. Since it can be deployed and reconfigured rapidly at very low cost, the ad hoc network is highly appealing for vast range of critical applications, such as military troop communication, disaster relief, daily information exchange, etc., and serves as an indispensable component among the next generation wireless networks [2]. To facilitate the application and commercialization of ad hoc networks, understanding their fundamental performance, especially the capacity of such networks, is of great importance.

In the landmark paper [3], Gupta and Kumar first made a breakthrough on the research of capacity performance for static ad hoc networks. They derived some important scaling law[1] results and indicated that the per node throughput will shrink to zero as the number of nodes tends

[1] The term of scaling law usually appears together with notations $(O, \Omega, \Theta, o, \omega)$ [4], and is used to describe the growth rate of the per node throughput as the number of nodes tends to infinity.

to infinity. Later, Li et al. [5] studied the impact of traffic pattern on the scaling law and demonstrated that the random traffic pattern applied in [3] leads the network to be unscalable, while the traffic pattern with a power law distance distribution can lead the network to be scalable. Grossglauser and Tse demonstrated in [6] that with the help of node mobility, a constant per node throughput is achievable in a mobile ad hoc network (MANET). Later, Neely and Modiano [7] revealed a fundamental tradeoff between the throughput capacity and packet delay in MANETs. Inspired by the above important studies, lots of work has been devoted to the capacity scaling analysis of ad hoc networks in the last decade. For a detailed survey on the corresponding results and research status, please kindly referred to [8, 9] and Sect. 6 for the related work.

It is notable that one common limitation of available studies on the throughput capacity of ad hoc networks is that to simplify their analysis, they usually assume the buffer size of each node is infinite (i.e., the packet loss due to buffer overflowing is neglected), which is not practical under a realistic network scenario, especially in some critical applications that the buffer size is very small due to the lack of node resource (limited node size, low computing capability, etc.). Thus, for the practical network performance analysis, the constraint on buffer size should be carefully addressed. By now, the throughput capacity of practical buffer-limited ad hoc networks still remains a technical challenge and is largely unknown.

As a step towards this end, in this paper we focus on a static large-scale ad hoc network where each node is equipped with a limited buffer, and analyze its corresponding capacity performance. The main contributions of this paper are summarized as follows.

- For the concerned ad hoc network where the buffer size of a node is B packets, we first model each node as a G/G/1/B queuing system which incorporates the important wireless interference and medium access contention.
- With the help of the proposed G/G/1/B queuing model, we then explore the properties of the throughput upper bound for all scheduling schemes.
- Based on these properties and queuing theory, we further develop an analytical approach to derive the expression of per node throughput capacity, as well as reveal the impact of buffer constraint on throughput performance.
- To demonstrate the throughput capacity can be achieved or approached, we finally provide some corresponding scheduling schemes under both symmetrical and unsymmetrical network topologies.

The remainder of this paper is organized as follows. The system models are introduced in Sect. 2. Section 3 develops the G/G/1/B queuing model and explores the properties of the throughput upper bound. The per node throughput capacity is derived in Sect. 4 and the corresponding specific scheduling schemes are presented in Sect. 5. Finally, Sect. 6 introduces the related work and Sect. 7 concludes this paper.

2 System models

This section presents the system models involved in this paper.

2.1 Network model

Similar to the previous studies [5, 10], we consider a static and time-slotted large-scale ad hoc network which consists of n nodes ($n \to \infty$) within a square region of area A. The locations of nodes follow the uniform distribution and the probability that there are k nodes within an unit area is $\binom{n}{k}\left(\frac{1}{A}\right)^k\left(1-\frac{1}{A}\right)^{1-k}$. We consider the network is extended, i.e, the network area extends as the number of nodes grows and the node density $\sigma = \frac{n}{A}$ is fixed. Each node in the network maintains one queue for storing the packets generated by itself and the packets of other nodes. The queue follows the FIFO (first-in-first-out) discipline[2] and its buffer size is normalized to B packets. When the queue is full, the packets arriving at this time are dropped directly.

2.2 Communication model

We adopt the widely used protocol model proposed in [3] to decide whether a transmission between two nodes is successful or not. Suppose that in a time slot node i transmits data to node j, as required by the protocol model, the transmission is successful if and only if the following two conditions hold:

1) $d_{i,j} \le r_0$;
2) for any other concurrent transmitter k, $d_{k,j} \ge (1+\Delta)r_0$, where r_0 is the common transmission radius of all nodes in the network, $d_{i,j}$ denotes the Euclidean distance between node i and node j, and $\Delta > 0$ models a guard zone to prevent the transmission from being interfered by other simultaneous transmissions.

We adopt this protocol model here mainly due to the following reasons. First, the mathematical tractability of this model allows us to gain important insights into the

[2] Please kindly notice that the queue discipline has no impact on the per node throughput performance.

structure of network performance analysis. Second, the analysis under this model provides a meaningful theoretical result in the limit of the network scenario where nodes within the interference range are allowed to transmit packets simultaneously.

We set the channel rate as W packets/slot, i.e., if a node get access to the wireless channel in a time slot, the amount of data will be transmitted in this time slot is W packets. All nodes in the network compete for the wireless channel through a fair media access control (MAC) protocol, such as the DCF-style mechanism [11].

2.3 Traffic model

We consider the widely adopted random traffic model with the power law distance distribution [5, 10]. With this traffic model, the probability $p(r)$ that two nodes maintain a routing-layer session (i.e., the nodes become a source-destination pair) is

$$p(r) = \begin{cases} \dfrac{2(\beta-2)}{\beta} \dfrac{r_0^{\beta-2}}{r^{\beta-1}}, & r > r_0 \\ \dfrac{2(\beta-2)}{\beta} \dfrac{r}{r_0^2}, & r \le r_0 \end{cases} \tag{1}$$

where r denotes the distance between the source and destination and β is a constant parameter. We assume the expected packet generating rate of each node is λ packets/slot. Since we focus on a large-scale ad hoc network, packets are delivered to their destinations by the multi-hop manner, and the number of hops h can be approximated as $h \approx \lceil \varepsilon r / r_0 \rceil$, where ε is a constant coefficient corresponding to the scheduling scheme adopted. For example, if the minimum-hop routing scheme is adopted, then $\varepsilon = 1$.

Please kindly notice that the power law traffic model is actually a near-domain traffic model, that is, a network node has a higher probability to select a node which is near from itself as its destination, and this model is more likely to be line with the practical network behaviors. It has been demonstrated in [5, 10] that the network is scalable with the power law traffic model when $\beta \ge 4$, and under this scenario, the analysis of the impact of buffer constraint on throughput performance is more intuitive. Moreover, the value of β does not influence the development of our theoretical approach for the throughput performance analysis in the following sections. Therefore, without loss of generality, we set the critical value $\beta = 4$ to ensure the scalability of network, as well as relax the near domain restriction on traffic model.

2.4 Basic definition

Per Node Throughput the *per node throughput* is defined as the time average of number of packets that can be received by a node which serves as a destination. More formally, considering a time interval [0, t], we denote by $m_i(t)$ the number of packets received by node i (all these packets are destine for node i), the per node throughput Th is defined as $Th = \lim_{t\to\infty} \frac{m_i(t)}{t}$. The throughput capacity is the achievable upper bound for the per node throughput.

Please kindly notice that in many previous works [6, 7] where the unicast traffic model (i.e., the packets generated at a source node are destined for only one destination) is adopted, the per node throughput is defined as the time average of number of packets that can be delivered from a source node to its destination, and it is also termed as per flow throughput. However, with our more practical multicast power law traffic model (i.e., the probability that two nodes maintain a routing-layer session follows a specific distribution), the per node throughput cannot be defined as the per flow throughput since a network node receive packets from multiple sources, and it is appropriate to define the per node throughput as the time average of number of packets that can be received by a destination.

3 Preliminaries

In this section, we first provide an intuition for the throughput performance under the buffer-limited network scenario, then present the G/G/1/B queuing model, and finally explore the properties of throughput upper bound, which will help us derive the per node throughput capacity in Sect. 4.

3.1 Intuition of throughput under buffer-limited network scenario

Regarding the throughput of a buffer-limited ad hoc network, we first provide a simple illustration to gain intuition. As shown in Fig. 1, there are two source nodes and each of which has λ packets destined for the same destination node. We denote by P_{B_i} the buffer overflowing probability (BOP) of relay node i (i.e., the probability that the buffer of relay node i is full), then the total amount of packets that can be delivered to the destination under the left-side scheduling scheme is $\lambda(1-P_{B_1}) + \lambda(1-P_{B_2})$, and that under the

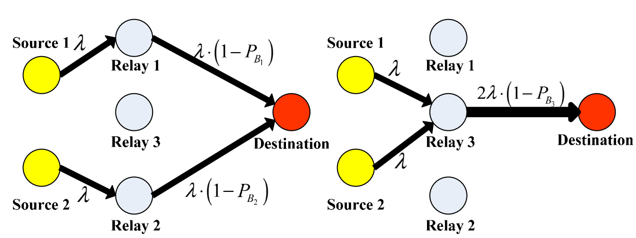

Fig. 1 Illustration for the throughput under buffer-limited network scenario

right-side scheduling scheme is $2\lambda(1 - P_{B_3})$. Notice that the two schemes lead to different traffic distributions on the network, which further lead to different BOPs of nodes, thus the amount of packets that can be delivered under the two schemes are different.

The observation here is that under the buffer-limited scenario, the distribution of traffic has an important effect on the throughput performance. Thus, for the capacity study of buffer-limited ad hoc networks, we should explore the scheduling scheme with the optimal traffic distribution, which can lead to the maximal achievable throughput. To address this issue, we then develop a G/G/1/*B* queuing model for each node to depict the highly dynamics of the packet arrival and departure processes.

3.2 G/G/1/*B* queuing model

As illustrated in Fig. 2, we model each node in the concerned network as a G/G/1/*B* queuing system [12] to depict its highly dynamic packet arrival and departure processes. The queuing system has a single server (i.e., the access to wireless channel for a node) and the buffer capacity is limited to *B* packets, the inter-arrival time and service time are independent and follow a general distribution. In order to obtain the corresponding stationary distribution of this queuing system, we need to derive its mean packet arrival rate and mean service rate. Without loss of generality, we only focus on one node (denoted by node i) in the following analysis.

Regarding the packet arrival process of node i, there are two types of packets will enter its queue: first, the packets that are self-generated at node i; second, the packets that are forwarded to node i from other nodes (but node i is not the destination of these packets). We denote by λ_i^f the expected arrival rate of the second type of packets at node i, and denote by g_i the total expected packet arrival rate of node i, then it is obviously that $g_i = \lambda + \lambda_i^f$.

Regarding the packet departure process of node i, we intend to derive its mean service rate μ. Considering that in a given time slot, node i and node k want to transmit data to node j and node l respectively, according to our communication model the receptions at node j and node l can be simultaneously successful if and only if the following conditions are satisfied.

$$d_{i,j} \le r_0 < (1 + \Delta) r_0 \le d_{k,j}, \tag{2}$$

$$d_{k,l} \le r_0 < (1 + \Delta) r_0 \le d_{i,l}. \tag{3}$$

Then we have

$$d_{j,l} \ge d_{i,l} - d_{i,j} \ge \Delta r_0, \tag{4}$$

$$d_{l,j} \ge d_{k,j} - d_{k,l} \ge \Delta r_0. \tag{5}$$

It indicates the essential condition of simultaneous successful transmissions is that the disks of radius $\frac{\Delta}{2} r_0$ centered at receivers cannot intersect with each other, as shown in Fig. 3.

Based on the above observation, we can conclude that due to the restriction of wireless interference, a successful reception at a node will consume a circle area in the network. We denote by n_s the maximal number of concurrent successful receivers that the network can support, then n_s is equal to the number of reception circles that the whole network area can contain. Notice that the area of a reception circle A_{rc} is

$$A_{rc} = \pi \left(\frac{\Delta r_0}{2} \right)^2 = \frac{\pi \Delta^2 r_0^2}{4}, \tag{6}$$

then we have

$$n_s = \frac{A}{A_{rc}} = \frac{4n}{\pi \sigma \Delta^2 r_0^2}. \tag{7}$$

Thus, the mean service rate of the G/G/1/*B* queuing system is given by

$$\mu = \frac{n_s}{n} \cdot W = \frac{4}{\pi \sigma \Delta^2 r_0^2} \cdot W. \tag{8}$$

Remark 1 It is notable that the important wireless interference and medium access contention have been carefully incorporated into the modeling of the G/G/1/*B* queuing system.

Regarding the BOP of node i with mean packet arrival rate g_i and mean service rate μ, we utilize an effective approximation method proposed in [13] to estimate the

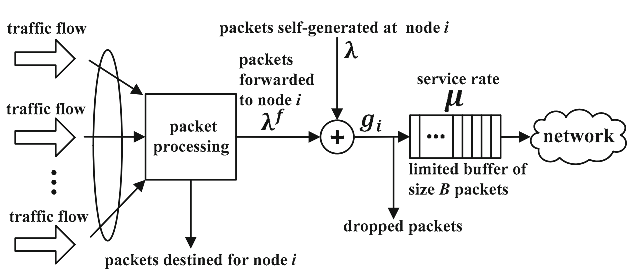

Fig. 2 Illustration of the G/G/1/*B* queuing model

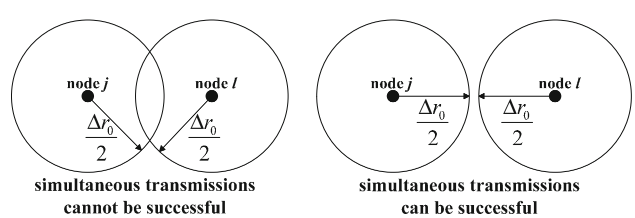

Fig. 3 Illustration of the essential condition of simultaneous successful transmissions

stationary distribution $\mathbf{\Pi} = \{\pi_0, \pi_1, \ldots \pi_B\}$ of the G/G/1/B queuing system, where π_k $(0 \le k \le B)$ denotes the probability that there are k packets in the buffer of node i when the network is in steady state. According to [13], $\mathbf{\Pi}$ can be approximated by the following recursions.

$$\begin{cases} \pi_1 = \pi_0 \dfrac{g_i}{b}\left\{\exp\left(\dfrac{2b}{a}\right) - 1\right\}, \\ \pi_k = \pi_0 \dfrac{g_i}{b}\exp\left\{\dfrac{2(k-1)b}{a}\right\}\left\{\exp\left(\dfrac{2b}{a}\right) - 1\right\}, \quad 2 \le k \le B-1 \\ \pi_B = \pi_0 \dfrac{g_i}{\mu}\exp\left\{\dfrac{2(B-1)b}{a}\right\}, \end{cases} \tag{9}$$

where $\exp(\cdot)$ is the exponential function, $a = g_i c_0 + \mu c_1$, $b = g_i - \mu$, and c_0, c_1 are constant parameters. Combining with the normalization formula $\sum_{k=0}^{B} \pi_k = 1$, π_k can be solved recursively. Then the corresponding BOP can be derived as

$$P_B = \pi_B = \frac{(\mu - g_i) g_i \Gamma}{\mu^2 - g_i^2 \Gamma}, \tag{10}$$

where $\Gamma = e^{2(B-1)b/a}$.

3.3 The properties of throughput upper bound

Based on the G/G/1/B queuing model for each node, we then explore the properties of the throughput upper bound of the concerned network.

We first provide the following lemma regarding a convex optimization issue.

Lemma 1 If $f(x)$ is a convex function, then for the following optimization,

$$\min \quad F(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n} f(x_i), \tag{11}$$

$$s.t. \quad x_1 + x_2 + \cdots + x_n = X > 0, \tag{12}$$

$$x_i \ge 0, \tag{13}$$

the optimal solution $\mathbf{x}^* = [x_1^*, x_2^*, \cdots, x_n^*]$ is

$$x_1^* = x_2^* = \cdots = x_n^* = \frac{X}{n}. \tag{14}$$

Proof We let $\mathbf{Z^n}$ denote the feasible region of the optimization (11). Since $\mathbf{x}^* = [x_1^*, x_2^*, \ldots, x_n^*]$ is the optimal solution of the optimization, then for $\forall \mathbf{x} \in \mathbf{Z^n}$ we have

$$\nabla F(\mathbf{x}^*)(\mathbf{x} - \mathbf{x}^*)^T \ge 0 \Leftrightarrow \sum_{i=1}^{n} f'(x)|_{x=x_i^*}(x_i - x_i^*) \ge 0, \tag{15}$$

where ∇ is the Del operator and $(\cdot)^T$ denotes the transpose of a vector.

Without loss of generality, we focus on a non-zero element $x_i^* > 0$ in the optimal solution and construct another feasible solution $\mathbf{x}$ as follow: we set $x_i = 0$, $x_j = x_i^* + x_j^*$ and $x_m = x_m^*$ for $m \ne i, j$. Substituting $\mathbf{x}$ into (15) we have

$$f'(x_i^*) \le f'(x_j^*). \tag{16}$$

Suppose that the element x_j^* in the optimal solution is 0, since $f(x)$ is a convex function and thus $f'(x)$ is monotonically increasing, we have $f'(x_i^*) > f'(x_j^*)$ which contradicts (16). Thus we can conclude that all the elements in the optimal solution are larger than 0, and combining with (16) we have

$$f'(x_1^*) = f'(x_2^*) = \cdots = f'(x_n^*),$$
$$\Leftrightarrow x_1^* = x_2^* = \cdots = x_n^* = \frac{X}{n}.$$

This completes the proof. □

The scheduling scheme of a network is defined as a set of schemes that the network operation follows. In our network scenario, a specific scheduling scheme includes a MAC scheme and a routing scheme. Regarding the MAC scheme, in our communication model and development of G/G/1/B queuing model, we assume a fair and distributed MAC scheme and the detailed operation of this scheme will be provided in Sect. 5.1. Regarding the routing scheme, it determines the traffic distribution on the network thus further determines the achievable throughput. Therefore, we provide the following theorem to reveal the properties of the optimal routing scheme which leads to a throughput upper bound for the concerned buffer-limited ad hoc networks.

Theorem 1 The throughput under the routing scheme with the following two properties can serve as an upper bound for that under all routing schemes: (a) the packet arrival rate at each node satisfies that $g_1 = g_2 = \cdots = g_n$; (b) all packets are forwarded through the minimum-hop path.

Proof We define all the routing schemes as the scheme set $\mathbf{S}$. For a specific scheme $S \in \mathbf{S}$, it causes a corresponding total network load G in steady state, i.e., $G = \sum_{i=1}^{n} g_i$. We denote by $\mathbf{S}(G_l)$ the subset of $\mathbf{S}$, in which all the schemes lead to the same network load G_l and we have $\mathbf{S} = \bigcup_{l=1}^{\infty} \mathbf{S}(G_l)$. Without loss of generality, we set $G_1 < G_2 < \cdots < G_l < \cdots$.

We define that a routing scheme is κ-short if the mean hops under this scheme is at most κ times of that under the minimum mean hop routing scheme, i.e.,

$$\kappa = \frac{\text{the mean hops under the specific routing scheme}}{\text{minimum mean hops}}. \tag{17}$$

It is obvious that $\kappa \in [1, \infty)$.

We first consider the issue that in a scheme subset $\mathbf{S}(G_l)$, which scheme S_l^* can maximize the rate of packets that actually enter the network. This issue is equivalent to the optimization issue as follow.

$$\max \quad F(g_1, g_2, \cdots, g_n) = \sum_{i=1}^{n} \lambda \cdot (1 - P_B(g_i))), \tag{18}$$

$$s.t. \quad g_1 + g_2 + \cdots + g_n = G_l, \tag{19}$$

$$g_i \geq 0. \tag{20}$$

From (10) we can see that $P_B(g_i)$ is a convex function, thus based on Lemma 1 S_l^* can be determined as

$$S_l^* : g_1^* = g_2^* = \cdots = g_n^* = \frac{G_l}{n}. \tag{21}$$

We then compare these optimal solutions in each subset. Under these routing schemes, F can be expressed as

$$F^*(G) \triangleq F^*|_{\sum_{i=1}^{n} g_i = G} = n\lambda \cdot \left(1 - P_B\left(\frac{G}{n}\right)\right). \tag{22}$$

Since $P_B(g_i)$ is monotonically increasing with g_i, then we have

$$F^*(G_1) > F^*(G_2) > \cdots F^*(G_l) > \cdots. \tag{23}$$

From another perspective there is

$$\kappa_l = \frac{\text{mean forwarding hops of } S_l^*}{\text{minimum mean hops}}, \tag{24}$$

and $G_1 < G_2 < \cdots < G_l < \cdots$, then we have

$$\kappa_1 < \kappa_2 < \cdots < \kappa_l < \cdots. \tag{25}$$

Since the minimum value of κ_l is 1, we can conclude that the rate of packets which actually enter the network under the routing scheme with the properties (a) and (b) serves as an upper bound. Meanwhile, it indicates the corresponding overflowing probability serves as a lower bound. Notice that in steady state, the network throughput can be expressed as $\lambda \cdot (1 - P_B)^h$, where h denotes the corresponding mean hops. It is obvious that under the scheme with the properties (a) and (b), the values of P_B and h reach their minimums simultaneously, and thus the corresponding throughput is an upper bound for all routing schemes. This completes the proof. □

4 Throughput capacity

With the help of G/G/1/B queuing model and the properties of the optimal scheduling scheme, in this section we derive the per node throughput capacity. Firstly, we present two useful lemmas.

Regarding the packet arrival rate, we have the following lemma.

Lemma 2 Under the optimal scheduling scheme, the packet arrival rate at each node $\overline{g}$ can be determined as

$$\overline{g} = \lambda + \frac{\lambda}{2} \cdot I(P_B), \tag{26}$$

where $I(x) = \sum_{i=1}^{\infty} \frac{(1-x)^i}{i^2}$, and $0 = I(1) \leq I(P_B) \leq I(0) = \frac{\pi^2}{6}$.

Proof Under the optimal scheduling scheme, the packet arrival rate at each node is equal and denoted by $\overline{g}$, and the corresponding BOP of each node is $P_B(\overline{g})$ and abbreviated as P_B if there is no ambiguity.

Without loss of generality, we focus on a tagged source node S. Consider that in a time slot, S generates λ packets which are destined for a node D with distance r apart. Due to the multi-hop characteristic of large-scale ad hoc networks, these λ packets will cause *extra* packet arrival on the corresponding relay nodes. As illustrated in Fig. 4, these packets will be dropped by the corresponding relay nodes when their buffers overflow, and from a statistical point of view, there are $\lambda(1 - P_B)$ packets will arrive at the first relay node, $\lambda(1 - P_B)^2$ packets will arrive at the second relay node, and so on.

Notice that under the optimal scheduling scheme, packets are forwarded on the minimum-hop path. Thus for a $S - D$ path with distance r, the contribution of λ packets to the whole network arrival rate is

$$\begin{aligned} C(\lambda|r) &= \lambda + \lambda(1 - P_B) + \lambda(1 - P_B)^2 \\ &\quad + \cdots + \lambda(1 - P_B)^{\lceil r/r_0 \rceil - 1} \\ &= \sum_{i=1}^{\lceil r/r_0 \rceil} \lambda(1 - P_B)^{i-1}. \end{aligned} \tag{27}$$

Substituting the traffic model (1) into (27), the mean contribution of λ packets to the network arrival can be determined as

$$\mathbb{E}\{C\} = \int_0^{\infty} P(r) \cdot \sum_{i=1}^{\lceil r/r_0 \rceil} \lambda \cdot (1 - P_B)^{i-1} dr, \tag{28}$$

and the total network load is

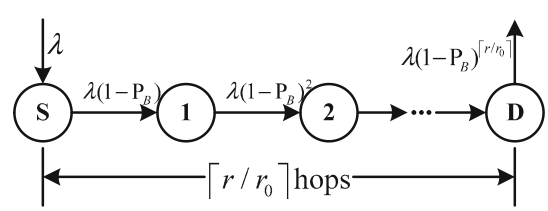

Fig. 4 Illustration of the impact of self-generated packets on the whole network

$$G = n \cdot \mathbb{E}\{C\}. \tag{29}$$

Thus under the optimal scheduling scheme, the packet arrival rate at each node is determined as

$$\begin{aligned}
\overline{g} &= \frac{G}{n} = \mathbb{E}\{C\} \\
&= \int_0^{r_0} \lambda \frac{r}{r_0^2} dr + \sum_{i=1}^{\infty} \int_{i \cdot r_0}^{(i+1)r_0} \lambda \frac{r_0^2}{r^3} \sum_{k=0}^{i} (1-P_B)^k dr \\
&= \frac{\lambda}{2} + \frac{\lambda}{2} \sum_{i=1}^{\infty} \left\{ \left(\frac{1}{i^2} - \frac{1}{(i+1)^2} \right) \cdot \sum_{k=0}^{i} (1-P_B)^k \right\} \\
&= \frac{\lambda}{2} + \frac{\lambda}{2P_B} f(P_B),
\end{aligned} \tag{30}$$

where

$$\begin{aligned}
f(P_B) &= \sum_{i=1}^{\infty} \left\{ \left(\frac{1}{i^2} - \frac{1}{(i+1)^2} \right) \cdot \left(1 - (1-P_B)^{i+1} \right) \right\} \\
&= 1 - \sum_{i=1}^{\infty} \left\{ \left(\frac{1}{i^2} - \frac{1}{(i+1)^2} \right) \cdot (1-P_B)^{i+1} \right\} \\
&= 1 - (1-P_B)^2 + P_B \cdot \sum_{i=2}^{\infty} \frac{1}{i^2} (1-P_B)^i \\
&= P_B \cdot (1 + I(P_B)).
\end{aligned} \tag{31}$$

Thus we have

$$\overline{g} = \frac{\lambda}{2} + \frac{\lambda}{2P_B} f(P_B) = \lambda + \frac{\lambda}{2} \cdot I(P_B).$$

This completes the proof. □

Remark 2 We can see from Eq. (26) that the packet arrival rate at each node consists of two parts, which is consistent with the modeling of packet arrival process in our G/G/1/B queuing system: the former part is the packets that are self-generated at a node, the residual is the packets that are forwarded to this node from other nodes. The BOP of a node determines its capability of accepting packets into its queue. When P_B approaches 1, there are few self-generated packets can pass through its own queue, so each node does not need to forward other nodes' packets, thus the actual packet arrival rate is equal to the packet generating rate. When P_B approaches 0, the packet arrival rate at each node is strictly bounded by $\lambda\left(1+\frac{\pi^2}{12}\right)$ even as the network size tends to infinite, indicating that the traffic model adopted in (1) can ensure the network scalability.

Notice that given a packet generating rate λ, Eq. (26) contains only one unknown quantity $\overline{g}$ (P_B is completely determined by $\overline{g}$), i.e., $\overline{g}$ is the fixed-point of Eq. (26) [14]. Thus, by solving this equation, we can determine $\overline{g}$ and P_B corresponding to a given λ.

Regarding the BOP when packet arrival rate approaches the service rate, we have the following lemma.

Lemma 3 When the packet arrival rate at each node approaches the service rate, i.e., $\overline{g} \to \mu$, the BOP can be express as

$$P_B^{\mu} \triangleq \lim_{\overline{g} \to \mu} P_B(\overline{g}) = \frac{c_0 + c_1}{2(c_0 + c_1 + B - 1)}. \tag{32}$$

Proof From (10) we have

$$\frac{1}{P_B(\overline{g})} = \frac{\mu^2 - \overline{g}^2 \Gamma}{(\mu - \overline{g})\overline{g}\Gamma} = \underbrace{\frac{\mu + \overline{g}}{\overline{g}\Gamma}}_{(a_1)} + \underbrace{\frac{\overline{g}(1-\Gamma)}{(\mu - \overline{g})\Gamma}}_{(a_2)}. \tag{33}$$

Since

$$\lim_{\overline{g} \to \mu} \Gamma = \lim_{\overline{g} \to \mu} \exp\left(\frac{2(B-1)(\overline{g} - \mu)}{\overline{g}c_0 + \mu c_1} \right) = 1, \tag{34}$$

and by utilizing the first-order Taylor expansion [15] there is

$$\Gamma \approx 1 + \frac{2(B-1)(\overline{g} - \mu)}{\overline{g}c_0 + \mu c_1} + o(\overline{g} - \mu). \tag{35}$$

Thus we have

$$\lim_{\overline{g} \to \mu} (a_1) = \lim_{\overline{g} \to \mu} \frac{2}{\Gamma} = 2, \tag{36}$$

$$\begin{aligned}
\lim_{\overline{g} \to \mu} (a_2) &= \lim_{\overline{g} \to \mu} \frac{\overline{g}\left(1 - 1 - \frac{2(B-1)(\overline{g} - \mu)}{\overline{g}c_0 + \mu c_1}\right)}{(\mu - \overline{g})\Gamma} \\
&= \lim_{\overline{g} \to \mu} \frac{2\overline{g}(B-1)}{(\overline{g}c_0 + \mu c_1)\Gamma} = \frac{2(B-1)}{c_0 + c_1}.
\end{aligned} \tag{37}$$

Combining (33), (36) and (37) we have

$$P_B^{\mu} = \left(2 + \frac{2(B-1)}{c_0 + c_1} \right)^{-1} = \frac{c_0 + c_1}{2(c_0 + c_1 + B - 1)}.$$

This completes the proof. □

Based on the Lemmas 2 and 3, we provide the following theorem regarding the per node throughput capacity in the buffer-limited ad hoc networks.

Theorem 2 For a concerned large scale ad hoc network where the number of nodes tends to infinity and each node has a buffer of size B packets, the per node throughput capacity T_c is determined as

$$T_c = \frac{1 - P_B^{\mu} - 0.5 P_B^{\mu} I(P_B^{\mu})}{1 + 0.5 I(P_B^{\mu})} \mu. \tag{38}$$

Proof For a given packet generating rate λ, we can determine the corresponding BOP P_B and packet arrival rate at each node $\overline{g}$ according to Lemma 2. Consider that a source-destination pair with distance r, the end-to-end packet loss ratio is $1-(1-P_B)^{\lceil r/r_0 \rceil}$, and the corresponding throughput is $\lambda \cdot (1-P_B)^{\lceil r/r_0 \rceil}$. Thus the expected per node throughput Th is determined as

$$\begin{aligned} Th &= \lambda \cdot \int_0^{\infty} P(r) \cdot (1-P_B)^{\lceil r/r_0 \rceil} dr \\ &= \lambda(1-P_B) - \frac{\lambda}{2} P_B I(P_B). \end{aligned} \tag{39}$$

When the packet arrival rate $\bar{g}$ approaches the packet service rate μ, according to formula (26) the corresponding packet generating rate λ^{μ} is determined as

$$\lambda^{\mu} = \frac{\mu}{1+0.5I(P_B^{\mu})}. \tag{40}$$

Substituting (40) into (39) we then have

$$\begin{aligned} Tc &= \lambda^{\mu}(1-P_B^{\mu}) - \frac{\lambda^{\mu}}{2} P_B^{\mu} I(P_B^{\mu}) \\ &= \frac{1-P_B^{\mu}-0.5P_B^{\mu}I(P_B^{\mu})}{1+0.5I(P_B^{\mu})}\mu. \end{aligned}$$

This completes the proof. □

Remark 3 Formula (39) provides us the insights of effects of buffer constraint on throughput performance. It can be seen that (39) consists of two parts: $\lambda(1-P_B)$ represents the packets which actually enter the network after generated at their source nodes; $\frac{\lambda}{2} P_B I(P_B)$ represents the packets dropped on the end-to-end route, which serves as the cumulative effect of packet loss due to the per hop buffer overflowing.

Based on Theorem 2, we further conduct simple mathematical derivations to provide a more intuitive expression of the per node throughput capacity with limited buffer constraint. From (38) we have

$$\begin{aligned} T_c &= \frac{1-P_B^{\mu}-0.5P_B^{\mu}I(P_B^{\mu})}{1+0.5I(P_B^{\mu})}\mu \\ &< (1-P_B^{\mu})\mu \qquad (41) \\ &= \left(1-\frac{c_0+c_1}{c_0+c_1+B-1}\right) \cdot \frac{2}{\pi\sigma\Delta^2 r_0^2} W + \frac{2}{\pi\sigma\Delta^2 r_0^2} W. \qquad (42) \end{aligned}$$

We can see in (42) that the buffer constraint does cause the degradation on per node throughput performance, compared with that under infinite buffer scenario (i.e., $B \to \infty$). The throughput performance degradation is caused by the cumulative effect of packet loss due to the per hop buffer overflowing, and is at least inversely proportional to the buffer size B.

Based on Theorem 2, we further provide numerical result to illustrate how the theoretical throughput capacity varies with the node buffer size. Without loss of generality, we set $\lim_{B\to\infty} T_c = 1$ by adjusting the basic network parameters such as W, σ, Δ and r_0 to appropriate values. We can observe from Fig. 5 that T_c monotonously increases as B increases. When B is small, T_c drops a lot compared with that under infinite buffer scenario, while with B getting larger and larger, the increment of T_c becomes smaller and smaller. This observation provides us a guideline for the practical ad hoc network design that by equipping nodes with appropriate buffer size (such as $B=10$ in Fig. 5), the ad hoc network can guarantee the throughput requirement, and at the same time save the networking cost.

5 Scheduling schemes

In this section, we provide appropriate scheduling schemes which enable the per node throughput to approach the corresponding upper bound. We first present the MAC scheme, and then present the routing schemes for symmetrical and unsymmetrical network topologies respectively.

5.1 Media access control

We consider that each node in the large-scale ad hoc network contends for the access to wireless channel using a DCF-style mechanism [11]. With the DCF-style mechanism, at the beginning of a time slot, each node uniformly selects an initial value from [0, CW] (CW denotes the contention window) and starts to count down. If a node doesn't hear any broadcasting message until its back-off counter reduces to 0, it broadcasts a message to claim itself as the transmitter among its local range; otherwise it stops

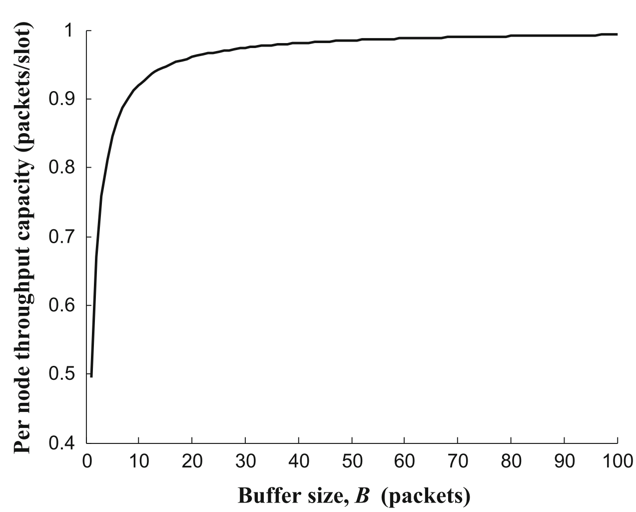

Fig. 5 Illustration of per node throughput capacity varying with buffer size in a large-scale ad hoc network

its back-off counter and remains silent in this whole time slot. Notice that the DCF-style mechanism adopted here is fair and highly distributed, thus it can facilitate the operations of ad hoc networks.

5.2 Routing scheme for symmetrical topology

As illustrated in Fig. 6 that in symmetrical network topologies, nodes are homogeneously distributed. Due to this special characteristic, we consider the routing scheme that when a node wants to transmit data to a corresponding destination, this node randomly selects a path among all possible minimum-hop paths with equal probability. Notice that with this routing scheme, packets are forwarded through the minimum-hop path, and the behavior of each node is same which further leads that the traffic distribution on each node is same. Therefore, the proposed routing scheme serves as the optimal routing scheme and the corresponding throughput capacity can be achieved.

5.3 Routing scheme for unsymmetrical topology

For the unsymmetrical topology, the minimum-hop routing scheme discussed above will lead to non-uniform traffic distribution on the network. To address this issue, we adopt here the Localized Circular Sailing Routing (LCSR) scheme which is proposed in [16] to balance the traffic distribution on the whole network, and at the same time ensure the packet forwarding hops are no more than a small constant times of that under the minimum-hop path.

By introducing a reverse stereographic projection mechanism [17], the LCSR scheme first projects nodes on the 2D plane to corresponding nodes on the 3D sphere. As illustrated in Fig. 7(a), node i in the network area is mapped to a point i' on the sphere according to the reversed stereographic projection. Then, the LCSR scheme makes routing selection based on the circular distance on the 3D sphere instead of the Euclidean distance on the 2D plane. For example, as illustrated in Fig. 7(b), consider that the source node in the network will send data to the destination node, the circular distance between the source-destination pair mapped on the sphere serves as the metric to execute routing selection. The shortest circular distance path is $Source' \rightarrow R_1' \rightarrow R_2' \rightarrow R_3' \rightarrow Des'$, then the corresponding actual routing in the network is selected as $Source \rightarrow R_1 \rightarrow R_2 \rightarrow R_3 \rightarrow Des$.

The simulation results in [16] show that the LCSR scheme can make the traffic almost uniformly distributed on the whole network, and the theoretical analysis in [16] indicates that the path length under LCSR scheme is no more than $\frac{\pi}{2}(1+\xi)$ times of that under the minimum-hop routing scheme, where the path expansion factor ξ is irrelevant with the number of nodes and ξ tends to 0 as the node distribution tends to be uniform. Therefore, the LCSR routing scheme serves as a suboptimal routing scheme and the throughput capacity could be approached.

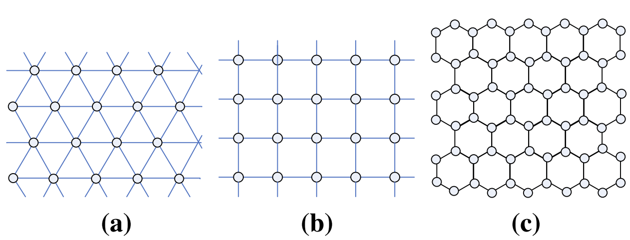

Fig. 6 Illustration of symmetrical network topologies. **a** Regular triangle. **b** Square. **c** Cellular

6 Related work

Since the seminal work of Gupta and Kumar [3], the throughput analysis for wireless ad hoc networks has been extensively reported in literature. It was demonstrated in

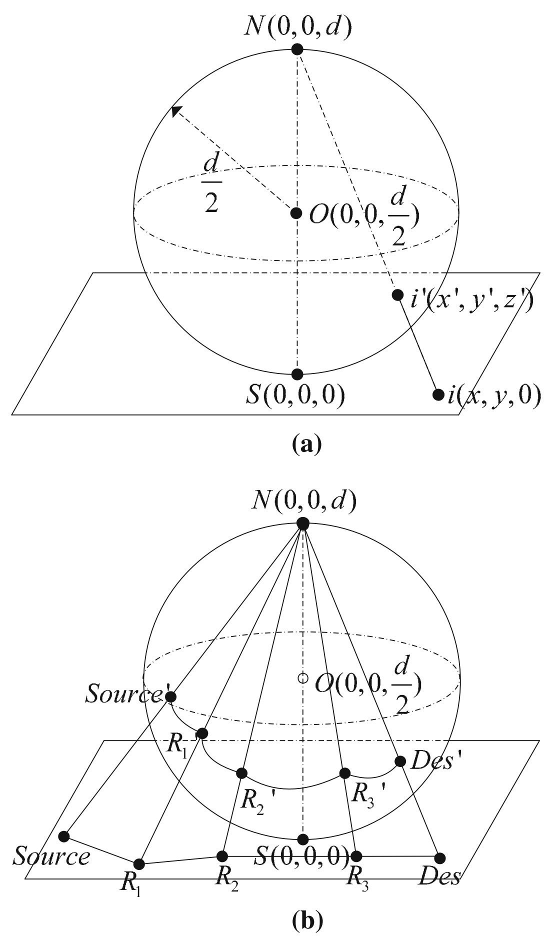

Fig. 7 Illustration of the LCSR routing scheme. **a** Reversed stereographic projection. **b** Routing selection

[3] that the per node throughput in a static ad hoc network with random traffic pattern will shrink to 0 as the number of nodes increases to infinity. Later, Li et al. [5] investigated the impact of traffic pattern on per node throughput scaling law. They indicated that the random traffic pattern will incur the capacity reducing to 0 as the network tends to infinity, while the traffic model with the power law distance distribution can ensure the network with the capacity scaling of $\Theta(1)$. Grossglauser and Tse [6] applied the node mobility to improve the capacity of MANETs. They demonstrated that with the help of node mobility, a $\Theta(1)$ per node throughput can be achieved in a MANET. Following this line, lots of work has been devoted to the analysis of throughput scaling law of MANETs under various mobility models [18–22]. Also, there are some studies focused on the scaling law of various network scenarios [23–27]. For a survey on the throughput scaling law results of wireless networks, readers are referred to [28] and references therein. Instead of deriving the per node capacity, some studies related to the general capacity region of ad hoc networks are reported in [29, 30]. With the development of 5G wireless communication networks, the studies on the capacity of ad hoc networks supported by the infrastructure have been recently shown in [31–33].

There are some initial works considered the throughput performance of ad hoc networks under the buffer constraint. Herdtner and Chong [34] made a heuristic analysis on the throughput storage tradeoff in MANET. They demonstrated that when the relay buffer of each node is limited, the per node throughput scaling law cannot achieve $\Theta(1)$ even through the node mobility is utilized for packet delivery. Subramanian et al. explored the throughput performance with buffer constraint in sparse delay tolerant networks (DTNs). They considered the unicast scenario in [35] and the multicast scenario in [36] respectively, and developed a theoretical framework to derive the corresponding throughput capacity. Recently, Liu et al. explored the throughput capacity and delay performance for buffer-limited mobile ad hoc networks, which can be seen in [37, 38].

7 Conclusion

This paper revisited the throughput capacity of ad hoc networks. By introducing the buffer constraint, our consideration is more in line with the actual network scenario. We modeled each node in the network as a G/G/1/B queuing system and with the help of this queuing model, we developed an analytical approach to derive the per node throughput capacity. The theoretical finding here is that the capacity degradation caused by buffer constraint is inversely proportional to the buffer size. As a complementary of the capacity analysis, we finally provided some appropriate scheduling schemes which can approach the throughput upper bound.

Notice that the theoretical analysis for per node throughput in this paper is based on the power law traffic model, so one of our future research directions is to develop theoretical study for other popular traffic patterns, such as the classic random traffic model. Moreover, with the development of wireless techniques such as network coding, some initial works have showed that nodes within interference range are allowed to transmit simultaneously, which has the great potential to improve the capacity of wireless ad hoc networks. Thus one of the future research directions is to extend our study to the performance analysis of ad hoc networks under more advanced interference models.

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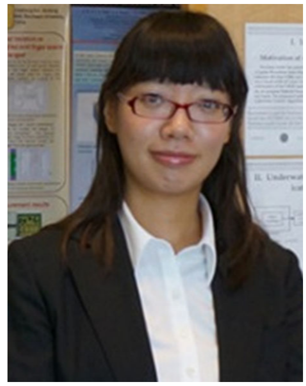
References

1. Perkins, C. E. (2008). *Ad hoc networking*. Boston: Addison-Wesley Professional.
2. Ramanathan, R., & Redi, J. (2002). A brief overview of ad hoc networks: Challenges and directions. *IEEE Communications Magazine*, *40*(5), 20–22.
3. Gupta, P., & Kumar, P. R. (2000). The capacity of wireless networks. *IEEE Transactions on Information Theory*, *46*(2), 388–404.
4. Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2009). *Introduction to algorithms*. Cambridge: MIT Press.
5. Li, J., Blake, C., De Couto, D. S., Lee, H. I., & Morris, R. (2001). Capacity of ad hoc wireless networks. In *Proceedings of the 7th annual international conference on mobile computing and networking* (pp. 61–69).
6. Grossglauser, M., & Tse, D. N. C. (2002). Mobility increases the capacity of ad hoc wireless networks. *IEEE/ACM Transactions on Networking*, *10*(4), 477–486.
7. Neely, M. J., & Modiano, E. (2005). Capacity and delay tradeoffs for ad hoc mobile networks. *IEEE Transactions on Information Theory*, *51*(6), 1917–1937.
8. Andrews, J., Shakkottai, S., Heath, R., Jindal, N., Haenggi, M., Berry, R., et al. (2008). Rethinking information theory for mobile ad hoc networks. *IEEE Communications Magazine*, *46*(12), 94–101.
9. Goldsmith, A., Effros, M., Koetter, R., Mdard, M., Ozdaglar, A., & Zheng, L. (2011). Beyond shannon: the quest for fundamental performance limits of wireless ad hoc networks. *IEEE Communications Magazine*, *49*(5), 195–205.
10. Zhou, N., Wu, H., & Abouzeid, A. A. (2005). The impact of traffic patterns on the overhead of reactive routing protocols. *IEEE Journal on Selected Areas in Communications*, *23*(3), 547–560.
11. Bianchi, G. (2000). Performance analysis of the IEEE 802.11 distributed coordination function. *IEEE Journal on Selected Areas in Communications*, *18*(3), 535–547.
12. Robertazzi, T. G. (2000). *Computer networks and systems: Queueing theory and performance evaluation*. Berlin: Springer Science & Business Media.
13. Takahashi, A., Takahashi, Y., Kaneda, S., & Shinagawa, N. (2007). Diffusion approximations for the GI/G/c/K queue. In *Proceedings of IEEE ICCCN* (pp. 681–686).

14. Granas, A., & Dugundji, J. (2003). *Fixed point theory*. Berlin: Springer Science & Business Media.
15. Stewart, J. (2011). *Calculus*. Boston: Cengage Learning.
16. Li, F., & Wang, Y. (2008). Circular sailing routing for wireless networks. In *Proceedings of IEEE INFOCOM* (pp. 1346–1354).
17. Coxeter, H. S. M. (1969). *Introduction to geometry*. New York: Wiley.
18. El Gamal, A., Mammen, J., Prabhakar, B., & Shah, D. (2006). Optimal throughput-delay scaling in wireless networks-part I: The fluid model. *IEEE Transactions on Information Theory*, *52*(6), 2568–2592.
19. Lin, X., Sharma, G., Mazumdar, R. R., & Shroff, N. B. (2006). Degenerate delay-capacity tradeoffs in ad-hoc networks with brownian mobility. *IEEE/ACM Transactions on Networking*, *14*(SI), 2777–2784.
20. Mammen, J., & Shah, D. (2007). Throughput and delay in random wireless networks with restricted mobility. *IEEE Transactions on Information Theory*, *53*(3), 1108–1116.
21. Sharma, G., Mazumdar, R., & Shroff, N. B. (2007). Delay and capacity trade-offs in mobile ad hoc networks: A global perspective. *IEEE/ACM Transactions on Networking*, *15*(5), 981–992.
22. Ciullo, D., Martina, V., Garetto, M., & Leonardi, E. (2011). Impact of correlated mobility on delay-throughput performance in mobile ad hoc networks. *IEEE/ACM Transactions on Networking*, *19*(6), 1745–1758.
23. Xie, L. L., & Kumar, P. R. (2004). A network information theory for wireless communication: Scaling laws and optimal operation. *IEEE Transactions on Information Theory*, *50*(5), 748–767.
24. Zhang, G., Xu, Y., Wang, X., & Guizani, M. (2010). Capacity of hybrid wireless networks with directional antenna and delay constraint. *IEEE Transactions on Communications*, *58*(7), 2097–2106.
25. Wang, X., Huang, W., Wang, S., Zhang, J., & Hu, C. (2011). Delay and capacity tradeoff analysis for motioncast. *IEEE/ACM Transactions on Networking*, *19*(5), 1354–1367.
26. Huang, W., & Wang, X. (2012). Capacity scaling of general cognitive networks. *IEEE/ACM Transactions on Networking*, *20*(5), 1501–1513.
27. Lee, S. H., & Chung, S. Y. (2012). Capacity scaling of wireless ad hoc networks: Shannon meets Maxwell. *IEEE Transactions on Information Theory*, *58*(3), 1702–1715.
28. Lu, N., & Shen, X. S. (2014). Scaling laws for throughput capacity and delay in wireless networks: A survey. *IEEE Communications Surveys & Tutorials*, *16*(2), 642–657.
29. Toumpis, S., & Goldsmith, A. J. (2003). Capacity regions for wireless ad hoc networks. *IEEE Transactions on Wireless Communications*, *2*(4), 736–748.
30. Urgaonkar, R., & Neely, M. J. (2011). Network capacity region and minimum energy function for a delay-tolerant mobile ad hoc network. *IEEE/ACM Transactions on Networking*, *19*(4), 1137–1150.
31. Law, L. K., Krishnamurthy, S. V., & Faloutsos, M. (2008). Capacity of hybrid cellular-ad hoc data networks. In *IEEE INFOCOM* (pp. 1346–1354).
32. Shila, D. M., & Cheng, Y. (2012). Ad hoc wireless networks meet the infrastructure: Mobility, capacity and delay. In *Proceedings of IEEE INFOCOM* (pp. 3031–3035).
33. Li, P., & Fang, Y. (2012). On the throughput capacity of heterogeneous wireless networks. *IEEE Transactions on Mobile Computing*, *11*(12), 2073–2086.
34. Herdtner, J. D., & Chong, E. K. (2005). Throughput-storage tradeoff in ad hoc networks. In *Proceedings of IEEE INFOCOM* (pp. 2536–2542).
35. Subramanian, R., Vellambi, B. N., & Fekri, F. (2009). A generalized framework for throughput analysis in sparse mobile networks. In *IEEE WiOPT* (pp. 1–10).
36. Subramanian, R., & Fekri, F. (2009). Analysis of multiple-unicast throughput in finite-buffer delay-tolerant networks. In *IEEE ISIT* (pp. 1634–1638).
37. Liu, J., Sheng, M., Xu, Y., Li, J., & Jiang, X. (2015). On throughput capacity for a class of buffer-limited MANETs. *Ad Hoc Networks*. doi:10.1016/j.adhoc.2015.08.029.
38. Liu, J., Sheng, M., Xu, Y., Li, J., & Jiang, X. (2015). End-to-end delay modeling in buffer-limited MANETs: A general theoretical framework. *IEEE Transactions on Wireless Communications*. doi:10.1109/TWC.2015.2475258.



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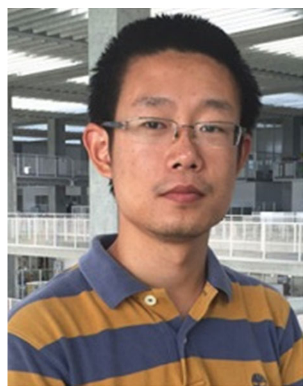

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