Received June 4, 2017, accepted July 3, 2017, date of publication July 7, 2017, date of current version July 24, 2017.

*Digital Object Identifier 10.1109/ACCESS.2017.2724059*

# Modeling Data Transport Capacity of Mobile Networks for Mobile Social Services

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This work was supported in part by the National Natural Science Foundation of China under Grant 61602110, in part by the Shanghai Sailing Program under Grant 16YF1400200, in part by the National Science Foundation for Postdoctoral Scientists of China under Grant 2016M591575, in part by the National Natural Science Foundation of China under Grant 61571331, in part by the Fok Ying-Tong Education Foundation for Young Teachers in the Higher Education Institutions of China under Grant 151066, in part by the Shuguang Program from Shanghai Education Development Foundation under Grant 14SG20, and in part by the Donghua Fundamental Research Funds for the Central Universities under Grant 2232016D-30.

**ABSTRACT** In this paper, we mainly study the data transport capacity of mobile networks for mobile social services. Specifically, mobile ad hoc social networks (MAHSNs) with infrastructure support are considered the carrier networks. In MAHSNs with infrastructure support, the underlying physical networks and the upper social relationship networks interact with each other and influence the capacity of this hybrid mobile social communication carrier network together. For the physical networks, we introduce a more practical clustered model to depict the social behavior of users. We consider a virtual home point for each mobile user. For the upper social relationship networks, we propose an improved population-based model, in which we map the home points of the mobile users into the social relationship formation, to solve the social formation problem in the mobile environment. This process comprehensively considers the clustering levels of the degree of friendship and friendship distribution. Finally, from a layered networking perspective, the geographical distribution of the social traffic sessions is analyzed to derive the capacity for social-broadcast sessions of MAHSNs with infrastructure support. The results provide deep insights into the impacts of a user' mobility pattern and social relationship formation on the capacity of MAHSNs with infrastructure support.

**INDEX TERMS** Mobile ad hoc social networks, infrastructure support, capacity, social-broadcast.

## I. INTRODUCTION

With the development of wireless communication technology and the popularity of mobile devices, an increasing number of social applications, such as WeChat, Facebook, and Twitter, have been exploiting smartphones and mobile notepads as their application terminals. On March 13th, 2014, the science and technology medium uTest indicated that the number of users of mobile APPs was greater than that of PCs for the first time. Obviously, mobile devices have become the main internet browsing terminal in the U.S., and the popularity of mobile social services continues to increase.

In mobile social services, various social applications run on certain types of mobile social carrier networks. In this paper, we take *mobile ad hoc social networks (MAHSNs) with infrastructure support* as a case study. Under this hybrid mobile communication carrier network, the infrastructure support presents certain advantages, such as high efficiency and centralized management, and the ad hoc way plays an important part in backbone offloading and privacy preserving.

Therefore, based on a hybrid communication architecture, it is worthwhile to investigate the fundamental limits of system performance, i.e., the optimal achievable performance. In this work, we primarily study the *network capacity*, which is a basic performance metric of the fundamental limits for data dissemination in MAHSNs with infrastructure support.

The capacity of MAHSNs with infrastructure support depends on the geographical characteristics of data dissemination sessions, i.e., the spatial distribution of traffic sessions. Compared with the general studies of wireless network capacity, social user mobility patterns in MAHSNs with infrastructure support will impact the formation of social relationships, and then the social relationships will influence the distribution of traffic sessions in the coupled network system [1], [2]. In this study, a particular challenge is: How to analyze the impacts of both users' behavior patterns and social relationships on the network capacity in the mobile environment under the hybrid communication architecture?

To solve this problem, we introduce a three-layered social network model [3]. The model presents a layered perspective for the social networks, consisting of a physical network layer, a social relationship layer and an application session layer, as shown in Fig. 1. Next, we formulate the corresponding models and show the correlations among the three layers.

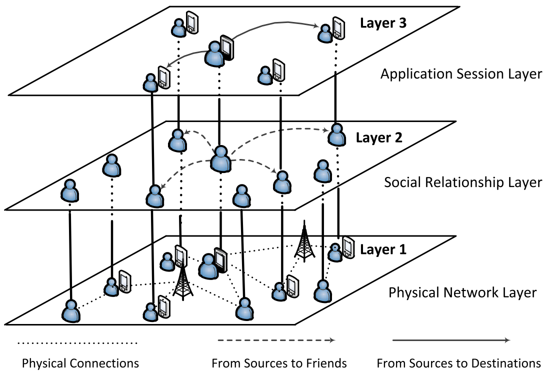



**FIGURE 1.** **Three-Layered Model [3].**

### A. PHYSICAL NETWORK LAYER

In mobile networks for mobile social services, mobile users usually form several social groups/clusters. To express the clustering phenomenon [4], we introduce a *clustered model* $(m(n), r(n))$ [5]–[7], in which $n$ denotes the number of users, $m(n)$ and $r(n)$ represent the number and the radius of clusters, respectively. For each user, we consider an important concept of *home point*, which is proposed by Garetto *et al.* [5] firstly. This concept is established according to the frequency of users' check-ins. The home point of a certain user represents the position of the maximal active probability of this user. Moreover, we define a *tension coefficient* $\eta(n) = n^{\varpi}$ to express the degree of mobility strength, where $\varpi \in [0, 1/2]$ is the *tension exponent*. Combining the network physical extension and the communication capability of node itself, we depict two cases, a *strong mobility* and a *weak mobility*, for MAHSNs with infrastructure support.

### B. SOCIAL RELATIONSHIP LAYER

According to the milestone study about the formation of social relationships [3], the distribution of a user's friends is related to the population density around this user in a particular distance. To be specific, the distribution obeys the *population-based model* $\mathcal{P}(\delta, \gamma, \beta)$, where $\delta \in [0, \infty)$ represents the clustering exponent of node distribution, $\gamma \in [0, \infty)$ represents the clustering exponent of friendship degree and $\beta \in [0, \infty)$ represents the clustering exponent of friendship formation. However, this formation model is only for static online social networks. In our paper, we propose an *improved* population-based social formation model. In the improved model, we let the stable home points of the mobile users map into the social relationship layer. Further, we let the mobile user independently choose its friends according to the population-based density function. It is important and effective that we use the underlying virtual home points to solve the social formation problem in a dynamic environment. The social formation model of static users [3], [8], [9] is extended to mobile users.

### C. APPLICATION SESSION LAYER

In mobile social applications, the most common scenario is that a person sends a message to all of his/her friends, such as posts on *Facebook*, *Foursquare*, *Sony PS Vita-Near Game*. Therefore, with respect to this application scenario, we study a typical traffic session, called *social-broadcast*, under which the source sends messages to all its friends formed on the basis of the improved social formation model. In the hybrid underlying architecture, the session occurs either via a node multi-hop between the source and its friends or via one hop to the base station backbone.

Under the three-layered system model, the contribution of our work can be summarized as follows:

- To derive the spatial distribution of traffic sessions in MAHSNs with infrastructure support, we construct a reasonable and practical model for mobile users relationship formation by introducing the home point policy in the clustered model. It improves the shortage caused by the impractical assumption of static and uniform nodes.
- To the best of our knowledge, this is the first work to investigate the capacity of MAHSNs with infrastructure support. We obtain the main results of the capacity for the networks. Besides, we also make research on the relationship between the capacity and the coefficient $\gamma, \beta$ in the population-based model $\mathcal{P}(\delta, \gamma, \beta)$. Through theoretical analyses and extensive simulations, we have concluded that a larger $\gamma$ and a larger $\beta$ can contribute to a larger network capacity for MAHSNs with infrastructure support.
- We use true data to validate the heterogeneous mobility and adopt the popular simulator to validate our theoretical results. The experiments not only verify the correctness of our theoretical results, but also bridge the math and the real with practical intuitions.

The rest of this paper is organized as follows. In Section II, we review previous studies and highlight the difference between our work and the related ones. In Section III, we construct each layer in the three-layered system model of MAHSNs with infrastructure support. In Section IV, we lay the basis for our subsequent proofs. Based on two different types of mobility cases, in Section V and Section VI, we obtain the social-broadcast capacity for strong and weak mobility cases from the ad hoc way and the cellular way, respectively. In Section VII, we do experiments to demonstrate the heterogeneous mobility phenomenon and validate the theoretical network capacity results. Finally, we conclude the paper in Section VIII.

## II. RELATED WORK

In previous studies of wireless network capacity, the groundbreaking work was Kumar and Gupta's research [10]. They showed that the per-node throughput is of order $\Theta(\frac{1}{\sqrt{n}})$

when $n \rightarrow \infty$. Then, to improve the network capacity, Grossglauser and Tse [11] made great progress by considering mobility. They proposed the store-carry-forward scheme to make the per-node capacity sustain the order $\Theta(1)$. Although it ignored delay, their work told us that mobility can improve the network capacity. Later, researchers studied many different mobility models for network performance analyses, such as the random walk mobility model [12], the Brownian mobility model [13], the random waypoint mobility model [14] and restricted/local mobility models [5], [7].

In addition to the mobility, infrastructure (in the hybrid network) is another intuitive way of increasing the network capacity. Liu *et al.* [15] proved that infrastructure could offer a linear capacity increase in hybrid network, when the number of base stations increased asymptotically faster than $\sqrt{n}$. Kozat and Tassiulas [16] proved that if the number of users served by each base station was bounded above, a per-node capacity of $\Theta(\frac{1}{\log n})$ could be achieved. Agarwal and Kumar [17] further extended this result to $\Theta(1)$. X-Y. Li et al. studied the multicast capacity in a static hybrid network by constructing a hybrid multicast routing tree [18], [19]. Wang *et al.* [20] studied the multicast capacity for hybrid wireless networks under Gaussian channel model. Depending on the number of base stations, nodes and destinations, the work analyzed the achievable multicast throughput in detail by selecting the optimal scheme. Recently, Qian *et al.* [6] and Huang *et al.* [21] studied the unicast and multicast capacities in a hybrid network under the clustered mobility model.

The above studies all focused on the general static/mobile wireless networks. They did not consider the effects of social interactions among nodes. The social network was first studied by Milgrams' experiments [22]. Later, Kleinberg [8] proposed a distance-based social model. After that, Liben-Nowell *et al.* [9] indicated that this model underestimated the inhomogeneity of users' geographical distributions and proposed a rank-based model. Recently, Wang *et al.* [3], in a milestone work, proposed a new social relationship formation model, called the population-based model. This model takes both distance and density into account and addressed the issue of network capacity for online social networks.

All in all, recent years have witnessed the popularity of mobile social services. It is significant for us to study the capacity of mobile networks for these services. From above studies, we can see that previous work on the capacity of general wireless networks does not consider the social relationship. Besides the latest studies on the capacity of wireless networks for mobile social services [3], [23], [24] are limited in using the ad hoc way in the static environment. To the best of our knowledge, our paper is the first work to study the capacity of mobile networks for mobile social services under the hybrid communication architecture. *Mobility, social relationship and hybrid communication architecture* are three important factors of our paper.

Especially, partial results of this work have been presented in our conference paper [25]. The difference between them is mainly in the communication architecture of the underlying carrier networks for mobile social services. The conference paper studies the social-broadcast capacity under the mobile ad hoc social networks (MAHSNs). This paper further extends the study to MAHSNs with infrastructure support. To be specific,

1) In this paper, we present some new results and related proofs of the social-broadcast capacity in MAHSNs with infrastructure support, including the upper and lower bounds analyses for strong and weak mobility cases through hybrid routing, respectively (Sec. V-C and Sec. V-D).
2) In this paper, we add extensive evaluations in a new Section VII. These experiments demonstrate the heterogeneous mobility and the theoretical capacity results derived in the paper.
3) In this paper, we add the construction method of the social relationship layer by using the home points in detail (Sec. III-B).
4) The contribution and the related studies of this work are rewritten.

## III. SYSTEM MODEL AND ASSUMPTION

In this section, we build the physical network layer, social relationship layer and application session layer respectively. We also provide the definition of the network capacity and introduce a special case for the clustered model.

### A. PHYSICAL NETWORK LAYER

As shown in Fig. 1, the bottom layer in our model is the physical network layer. In this layer, we construct the mobility model and the communication model to depict the underlying physical architecture of mobile ad hoc social networks (MAHSNs) with infrastructure support.

#### 1) MOBILITY MODEL

To model the MAHSNs with infrastructure support, the network area is treated as a torus $\mathcal{O}$ with wrap-around conditions, and $n$ wireless users move on its surface and $m$ static base stations form the network backbone. Let $X_i(t)$ denote the position of $i$th mobile user at time $t$; let $Y_i(t) \equiv Y_i$ denote the position of $i$th base station. When referring to both mobile users and base stations, we use notations $Z_i(t), 1 \leq i \leq n+m$ to label their positions. In this paper, we normalize the network area to 1 for convenience.

We assume that the bandwidth of the wireless channel is $W$ and the bandwidth of the wired links among base stations is $W_{base}$. Further, we divide the wireless resource $W$ into uplink bandwidth $W_{up}$ and downlink bandwidth $W_{down}$.

The mobility of users has been reported to present a spatially inhomogeneous property [6], [7], [21]. Long-term tracing experiments [26], [27] indicate that a user most often moves in a certain small region. It moves far away from this region with low probability. This phenomenon reflects the mobility restriction. Moreover, researchers found that some users like to aggregate in some areas. User density is higher in these aggregated areas and lower in other areas. It causes an uneven density distribution. This inhomogeneous phenomenon is evident particularly in the mobile social services due to the social relationships among users.

In order to describe the inhomogeneity, we give the following assumptions and settings.

- First, according to users' mobility restriction, we assume that each mobile user $v_i$ has a *home point*, which is denoted by $X_i^h$ and is located in the center of the small region. $X_i^h$ represents the position of the maximal active probability for mobile user $v_i$. Besides, we let the home point of the base station to be its static position.
- Second, we define a *tension coefficient* $\eta(n) = n^{\varpi}$ to express the degree of mobility strength, where $\varpi \in [0, 1/2]$ represents the *tension exponent* [7]. The tension can be seen as the pull of a rubber band that is fixed at the home point. When the tension coefficient is large, the pull of the rubber band is strong, which makes it difficult for the mobile user to move far; thus, the mobility is considered weak. On the contrary, when the coefficient is small, we consider the mobility to be strong. The tension coefficient reflects the node's ability to move away from its home point.
- Then, we characterize the density function of mobile user $v_i$ around $X_i^h$ by a function $\phi_i(X)$,

$$\phi_i(X) = \phi(X - X_i^h) = \frac{s(\eta(n)\|X - X_i^h\|)}{\int_{\mathcal{O}} s(\eta(n)\|X - X_i^h\|)dX},$$

  where $s(\eta(n)\|X - X_i^h\|)$ represents a non-increasing continuous function and $\|X - X_i^h\|$ denotes the Euclidean distance between mobile node $v_i$ and its home point.
- Finally, we introduce a *clustered model* [5]–[7], denoted by a two-tuples $(m(n), r(n))$, in which $m(n) = \Theta(n^{\epsilon})$ denotes the number of clusters, with $\epsilon \in [0, 1]$), and $r(n) = \Theta(n^{-\varrho})$ denotes the radius of a cluster, with $\varrho \in [0, \infty)$. Especially, when $m(n) = n$, it is a special case. We cast $m(n)$ cluster centers to the network area uniformly and independently with the radius $r(n)$. Then, $n$ home points are randomly assigned to these clusters uniformly. After that, we make each mobile node match to its home point correspondingly. Therefore, each mobile node can belong to the different clusters. For convenience in the paper, we place $m$ base stations regularly in the network area.

### 2) MOBILITY DEGREE AND COMMUNICATION

The defined tension coefficient shows that the intensity of node mobility is different. Some mobile users can move far away from their home points to transmit messages, but some only can move near around the home points. To combine the intensity of node mobility with network communication, mobility can be divided into two cases: a strong mobility case and a weak mobility case [7].

We first define a *critical transmission range* $\tau(n)$. It stands for the minimal transmission range that would guarantee network connectivity in the case that the nodes remain at their home points. According to the clustered model, we have $\tau(n) = \sqrt{\log(m(n))/m(n)}$.

We then define two types of mobility cases as follows:

**Case 1**: When $\tau(n) = o\left(\frac{1}{\eta\ (n)}\right)$, we consider it as a *strong mobility case*.

From the density function $\phi_i(X)$, we know that the denominator $\int_{\mathcal{O}} s(\eta(n)\|X - X_i^h\|)dX$ is of order $\frac{1}{\eta(n)^2}$. So the mobility of the mobile user is roughly limited to radius of $\Theta\left(\frac{1}{\eta(n)}\right)$. In this case, it is sufficient for the critical transmission range to reach $\frac{1}{\eta\ (n)}$. Thus, mobility plays an important role in exchanging data, and this case can take full advantage of mobility to improve the network capacity as much as possible.

**Case 2**: When $\tau(n) = \omega\left(\frac{1}{\eta\ (n)}\right)$, we consider it as a *weak mobility case*.

In this case, the critical transmission range must have to reach $\frac{1}{\eta\ (n)}$ at least. Here, because the nodes do not move far away or remain still, the effect of mobility on the network performance is reduced. The network connectivity mainly depends on the transmission range of each node instead of the node mobility.

### 3) INTERFERENCE MODEL

In the paper, we introduce the interference model from literature [10]. We use $\{X_k(t); k \in \mathcal{T}\}$ to represent the subset of nodes simultaneously transmitting at time $t$, and notation $\mathcal{T}$ denotes a set of node subscripts. A successful transmission will take place from node $v_i$ to $v_j$ at time $t$ only if:

$$\text{SINR} = \frac{\frac{P}{\|X_i(t)-X_j(t)\|^{\alpha}}}{N_0 + \sum_{k\in\mathcal{T},k\neq i} \frac{P}{\|X_k(t)-X_j(t)\|^{\alpha}}} \geq \xi,$$

where $N_0$ is the ambient noise power at the receiver, $P$ is the transmission power level, $\alpha > 2$ is a signal attenuation factor and $\xi$ represents the minimum value of SINR needed for a successful reception at destination node $v_j$.

## B. SOCIAL RELATIONSHIP LAYER

The middle layer is the social relationship layer. In this layer, we make some improvements on this model according to the *population-based model* proposed in the online social networks [3], to accommodate MAHSNs with infrastructure support.

From the physical network layer, we know that users are mobile and non-uniform; however, the home point of each user is relatively stable. Therefore, we map these home points into the social relationship layer. Thus, each mobile user $v_i$ in the physical network layer can correspond to a stable home point in the social relationship layer. This improvement is important for us to apply the population-based social formation model into our mobile social environment. Next, we will construct the improved population-based social formation model and provide some useful conclusions.

• Degree Distribution of Social Relationships

Let $q_i$ denote the number of friends of user $v_i$. Previous study [3] indicates that $q_i$ obeys Zif's distribution, i.e., $Pr(q_i = l) = (\sum_{j=1}^{n-1} j^{-\gamma})^{-1} \cdot l^{-\gamma}$, where $\gamma$ represents the clustering exponent of friendship degree, and $l \in N^+$.

• Density Function for Choosing Friends

Let the position of user $v_i$ represent the reference point. Then we choose $q_i$ points independently in the torus region $\mathcal{O}$ according to a probability distribution. Previous study [3] indicates that the probability that a point $p_{i_k}$ will be chosen as a candidate friend point of user $v_i$, satisfies a probability function with $[N(v_i, |p_{i_k} - v_i|) + 1]^{-\beta}$, where $\beta$ represents the clustering exponent of friendship formation, and $N(v_i, |p_{i_k} - v_i|)$ denotes the number of home points contained in the circle region with radius $|p_{i_k} - v_i|$. We let $\{p_{i_k}\}_{k=1}^{q_i}$ denote the set of these $q_i$ points. Fig. 2 illustrates the process of selecting a candidate friend point $p_{i_k}$ for user $v_i$.

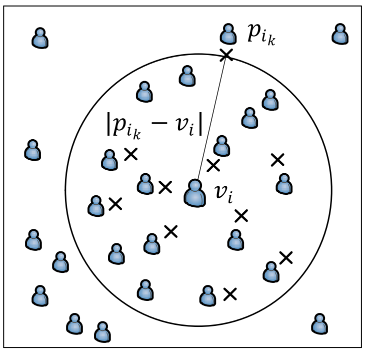



**FIGURE 2. Choosing friend points.**

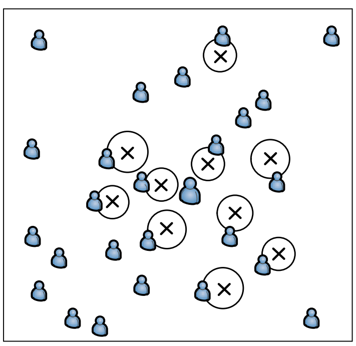


**FIGURE 3. Nearest principle.**

Finally, using the nearest principle, for each point in set $\{p_{i_k}\}_{k=1}^{q_i}$, we pick a home point that is nearest to point $p_{i_k}$. So we can independently determine $q_i$ corresponding mobile users (associating with $q_i$ home points) as the friends of user $v_i$ as shown in Fig. 3.

### C. APPLICATION SESSION LAYER

The upper layer is the application session layer. In this layer, different applications determine different social sessions.

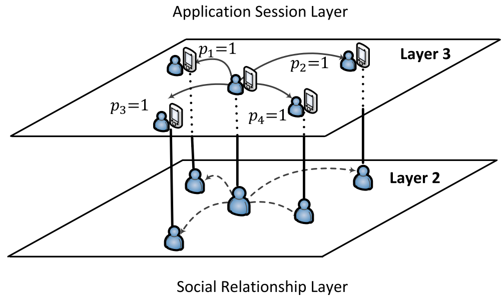



**FIGURE 4. Construction of social relationship layer.**

In this paper, we study a common session pattern, called social-broadcast, in which the source node sends packets to all its friends. From the model, we know that one source node $v_i$ has $q_i$ friends. Therefore, under the social-broadcast, the source node $v_i$ will deliver messages to all its $q_i$ friends with equal probability 1, as shown in Fig. 4.

We denote a set of communication nodes moving in the network $\mathcal{O}$ by $\mathcal{V} = \{v_1, v_2, ..., v_i, ..., v_n\}$. The corresponding home points for all nodes is denoted by a set $\mathcal{X}^h = \{X_1^h, X_2^h, ..., X_i^h, ..., X_n^h\}$.

Then, we define a social-broadcast session as $\mathcal{S}_i := \{v_i\} \cup \mathcal{F}_i$, where $v_i$ represents the source node and $\mathcal{F}_i$ represents the set of $v_i$'s friends, with $\mathcal{F}_i = \{v_{i_k}\}_{k=1}^{q_i}$ [3].

Correspondingly, we have a social-broadcast session notated by home points as follows: $\mathcal{S}'_i := \{X_i^h\} \cup \mathcal{X}_{i_k, \mathcal{F}}^h$, where the set $\mathcal{X}_{i_k,\mathcal{F}}^h = \{X_{i_1,\mathcal{F}}^h, X_{i_2,\mathcal{F}}^h, ..., X_{i_{q_i},\mathcal{F}}^h\}$ represents the home points of all friends of source node $v_i$.

### D. NETWORK CAPACITY FOR SOCIAL SESSIONS

For all social sessions, we suppose that packets arrive at each node at a rate of $\lambda$ packets per time-slot. The network is stable if and only if there exists a scheduling scheme which can guarantee the queue in each node does not increase to infinity as time goes to infinity. Thus, the per-node capacity of a network is the maximum arrival rate $\lambda$ that the network can stably support.

### E. SPECIAL CASE FOR CLUSTERED MODEL

In this work, we concentrate on studying a special case in which the home points of the mobile users are distributed uniformly and independently in the area. In this special case, we derive the number of clusters $m(n) = n$ and we also have $\tau(n) = \sqrt{\log m(n)/m(n)} = \sqrt{\log n/n}$. Correspondingly, in the population-based model $\mathcal{P}(\delta, \gamma, \beta)$, the clustering exponent $\delta$ of the node distribution is equal to zero. Thus, we specifically reduce the complexity from three dimensions $(\delta, \gamma, \beta) \in [0, \infty)^3$ to two dimensions $(\gamma, \beta) \in [0, \infty)^2$. In the future, we will study the general case in which $m(n) = \Theta(n^\epsilon)$, $\epsilon \in [0, 1)$, and $\delta \neq 0$. For convenience, we list some mainly used notations in TABLE 1.

**TABLE 1.** Main notations used in this paper.

| Notations | Meaning |
|---|---|
| $n$ | the number of mobile users |
| $m$ | the number of base stations |
| $X_i(t)$ | the position of mobile user $v_i$ at time $t$ |
| $X_i^h$ | the home point of mobile user $v_i$ |
| $\eta(n)$ | tension coefficient |
| $\varpi$ | tension exponent |
| $m(n)$ | the number of clusters |
| $r(n)$ | the radius of a cluster |
| $\tau(n)$ | critical transmission range |
| $q_i$ | the number of friends for mobile node $v_i$ |
| $\mathcal{P}(\delta, \gamma, \beta)$ | the population-based model |
| $\delta$ | clustering exponent of mobile node distribution |
| $\gamma$ | clustering exponent of friendship degree |
| $\beta$ | clustering exponent of friendship formation |
| $Q(\gamma)$ | the order of the number of all mobile nodes' friends |
| $H(\gamma, \beta)$ | the length bound of all social-broadcast sessions' Euclidean (Minimum) Spanning Tree |
| $\mathcal{V}$ | the set of all mobile nodes |
| $\mathcal{X}^h$ | the set of all mobile nodes' home points |
| $\mathcal{S}_i$ | a social-broadcast session for mobile node $v_i$ |
| $\mathcal{F}_i$ | the set of node $v_i$'s friends |
| $\mathcal{X}^h_{i_k,\mathcal{F}}$ | the set of home points for node $v_i$'s all friends |
| $\mu_{ij}^{\mathcal{S}}$ | the link capacity between node $v_i$ and $v_j$ under scheduling scheme $\mathcal{S}$ |
| $\mathcal{S}^\sharp$ | scheduling scheme under strong mobility case |
| $\mathcal{S}^\flat$ | scheduling scheme under weak mobility case |
| $\lambda$ | per-node social-broadcast capacity |
| $W$ | the bandwidth of the wireless channel |
| $W_{up}$ | the uplink bandwidth of the wireless channel |
| $W_{down}$ | the downlink bandwidth of the wireless channel |
| $W_{base}$ | the bandwidth of the wired links among base stations |

## IV. PRELIMINARIES OF SOCIAL-BROADCAST CAPACITY IN MAHSNS WITH INFRASTRUCTURE SUPPORT

To improve the network capacity, we select the ad hoc routing and the cellular routing adaptively. In Section V and Section VI, we will obtain the capacity of the networks from both the ad hoc and the cellular perspectives.

*Lemma 1 [6]: Suppose that $\{Z_i^h, 1 \leq i \leq n+m\}$ is deployed on $\mathcal{O}$ according to $(m(n), r(n))$ clustered model. The area of $\mathcal{O}$ is divided by regular tessellations. Each tessellation element has the area of $|A_{tes}| \geq (16+\zeta)\tau^2(n)$, for some small $\zeta > 0$, and defined with $N_h(A_{tes})$ the number of home points for both base stations and mobile users inside $A_{tes}$, then uniformly over the tessellations w.h.p. $N_h(A_{tes})$ is between $\frac{n|A_{tes}|}{2}$ and $2n|A_{tes}|$, i.e., $\frac{n|A_{tes}|}{2} < \inf N_h(A_{tes}) \leq \sup N_h(A_{tes}) < 2n|A_{tes}|$.*

*Definition 1 (Link Capacity [6]): The link capacity between node $v_i$ and $v_j$ is defined by the maximal long term data flow between them:*

$$\mu_{ij}^{\mathcal{S}} = E[1_{(i,j)\in\pi^{\mathcal{S}}(t)}|\mathcal{F}_{ij}],$$

*where $\pi^{\mathcal{S}}(t)$ is a selected set of node pairs that can simultaneously transmit at time $t$ under a stationary ergodic scheduling scheme $\mathcal{S}$; and $\mathcal{F}_{ij}$ is the Borel-field generated by the home points of base stations and mobile users. Link capacity represents the maximal traffic flow between node $v_i$ and node $v_j$.*

*Lemma 2: A network is divided into two regions $I_{\mathcal{L}}$ and $E_{\mathcal{L}}$ by using an arbitrary simple, regular and closed curve $\mathcal{L}$. According to the Maximum Concurrent Flow problem over the associated Generalized Random Geometric Graph (GRGG) [5], we have*

$$\lambda \leq \frac{\sum_{i:X_i^h\in I_{\mathcal{L}}}\sum_{j:X_j^h\in E_{\mathcal{L}}}\mu_{ij}}{\sum_{s:X_s^h\in I_{\mathcal{L}}}\sum_{d:X_d^h\in E_{\mathcal{L}}}\lambda_{sd}},$$

*where the denominator represents the number of social-broadcast flows passing through the curve $\mathcal{L}$; and the numerator represents the maximum total traffic crossing the curve $\mathcal{L}$.*

## V. SOCIAL-BROADCAST CAPACITY FOR STRONG MOBILITY CASE

In this section, we consider a social-broadcast session $\mathcal{S}_i := \{v_i\}\cup\mathcal{F}_i$. We also have the corresponding home point session $\mathcal{S}'_i := \{X_i^h\} \cup \mathcal{X}^h_{i_k,\mathcal{F}}$. We discuss the strong mobility case under the condition $\tau(n) = o\left(\frac{1}{\eta(n)}\right)$. In this case, we first give the upper and lower bounds of the social-broadcast capacity from the ad hoc perspective **(Theorem 1 and Theorem 2)**; we then obtain a tight bound of social-broadcast capacity from the ad hoc perspective **(Theorem 3)**; we next describe the upper and lower bounds of social-broadcast capacity from the cellular perspective (**Theorem 4 and Theorem 5**); finally, we obtain a tight bound of social-broadcast capacity by hybrid routing **(Theorem 8)**.

### A. SOCIAL-BROADCAST CAPACITY FOR STRONG MOBILITY CASE FROM AD HOC PERSPECTIVE

#### 1) UPPER BOUND

We introduce a proper scheduling scheme $\mathcal{S}^\sharp$ under the strong mobility case. In previous studies, especially those using mobility to increase the overall capacity, the transmission range can not be increased too much because it incurs substantial interference over the possible concurrent transmissions. Therefore, the transmission range should be reduced to an appropriate value that can both guarantee the network connectivity and maximize the overall capacity. Based on previous research, we choose $R_T = \Theta(\frac{1}{\sqrt{n}})$ as the transmission range in the strong mobility case. When two nodes move close to each other at a distance of $\Theta(\frac{1}{\sqrt{n}})$, they can exchange data directly.

*Definition 2 (Scheduling Scheme $\mathcal{S}^\sharp$): Given a network $\mathcal{O}$ comprising $n$ ad hoc nodes moving on its surface, scheduling scheme $\mathcal{S}^\sharp$ enables transmission between node $v_i$ and node $v_j$ when the following conditions are satisfied:*

$$d_{ij}(t) < R_T = \frac{c_1}{\sqrt{n}},$$
$$\min(d_{kj}(t), d_{ki}(t)) > (1+\Delta)R_T,$$

*where $d_{ij}(t)$ denotes the Euclidean distance between the home points of nodes $v_i$ and $v_j$ at time $t$; $c_1$ is a constant. This scheme is similar to the Protocol Model. For every other node $v_k$ in the simultaneously transmitting, the quantity $\triangle$ is a guard zone that prevents simultaneous transmission in this guard area.*

In the physical network layer, the mobility models built in this paper and in literature [6] are all home point based models. It has been proved in literature [5] that the scheduling scheme $\mathcal{S}^\sharp$ which uses $\Theta(\frac{1}{\sqrt{n}})$ as transmission range for mobile users is optimal.

*Lemma 3 [5]: In strong mobility case $\tau(n) = o(\frac{1}{\eta(n)})$, under the scheduling scheme $\mathcal{S}^\sharp$, for any pair of nodes $(i, j)$ and any finite $c_1 > 0$, we have the link capacity*

$$\mu_{ij}^{\mathcal{S}^\sharp} = \Theta(\Pr\{d_{ij} \le \frac{c_1}{\sqrt{n}} | \mathcal{F}_{ij}\}),$$

*where $d_{ij}$ denotes the Euclidean distance between the home points of nodes $v_i$ and $v_j$.*

*From the derivation in literature [5], we further obtain:*

$$\mu_{ij} = \Theta(Wg(n)\theta(\eta(n)\|X_j^h - X_i^h\|)),$$

*and*

$$\sum_{i:X_i^h \in I_\mathcal{L}} \sum_{j:X_j^h \in E_\mathcal{L}} \mu_{ij}$$

$$\le Wn^2 g(n) \int_{X\in I_\mathcal{L}} \int_{Y\in I_\mathcal{L}} \theta(\eta(n)\|X - Y\|) d_X d_Y,$$

*where $g(n) = \pi c_1^2 \frac{\eta^2(n)}{n}$ and $\theta(\|Y\|) = \int_{X\in R} s(\|X - Y\|) s(\|X\|) dX$.*

*Lemma 4 [5]: Under the assumption $\int x^3\theta(x)d_x < \infty$, for any convex, simple, regular, closed curve $\mathcal{L}$, we have*

$$\eta^2(n) \int_{X\in I_\mathcal{L}} \int_{Y\in E_\mathcal{L}} \theta(\eta(n)\|X - Y\|) d_X d_Y = \Theta(\frac{1}{\eta(n)}).$$

*Theorem 1: Given a network $\mathcal{O}$ consisting of n mobile ad hoc nodes, in strong mobility case, the upper bound of per-node social-broadcast capacity can be achieved by*

$$\lambda = O\left(\frac{Wn}{H(\gamma, \beta)\eta(n)}\right).$$

*Proof:* Let $l_{b,a}$ denote the side of the $a$th edge of the $b$th social-broadcast session. The probability that $l_{b,a}$ will pass through $\mathcal{L}$ (Lemma 2) is $l_{b,a} \cos \psi_{b,a}$, with $\psi_{b,a}$ representing the horizonal angle of $l_{b,a}$.

A random variable $\varepsilon_{b,a}$ is defined as follows:

$$\varepsilon_{b,a} = \begin{cases} 1 & \text{when } l_{b,a} \text{ crossing } \mathcal{L}, \\ 0 & \text{when } l_{b,a} \text{ without crossing } \mathcal{L}. \end{cases}$$

The number of social-broadcast flows crossing $\mathcal{L}$ is denoted by

$$N_\mathcal{L} = \sum_{s:X_s^h \in I_\mathcal{L}} \sum_{d:X_d^h \in E_\mathcal{L}} \lambda_{sd}.$$

The source node $v_i$ has $q_i$ friends, in which $q_i$ is a variable that obeys Zif's distribution defined in Section III-B. Here, we can obtain

$$N_\mathcal{L} = E(\sum_{b=1}^{n}\sum_{a=1}^{q_i} \varepsilon_{b,a}) = \sum_{b=1}^{n}\sum_{a=1}^{q_i} E(\varepsilon_{b,a})$$
$$= \sum_{b=1}^{n}\sum_{a=1}^{q_i} l_{b,a} \cos \psi_{b,a}.$$

Then, using Lemma 6 in literature [3], the length of all sessions in the population-based model is

$$\sum_{b=1}^{n} |EMST(\mathcal{S'}_b)| = \Omega(H(\gamma, \beta)),$$

where *EMST* denotes the Euclidean Minimum Spanning Tree, and $H(\gamma, \beta)$ is a sectional function. The value of $H(\gamma, \beta)$ is approximately of the order $n$, which varies with different values of $\gamma$ and $\beta$. We list the results of $H(\gamma, \beta)$ in TABLE 2.

**TABLE 2. $H(\gamma, \beta)$ in bounding $\sum$*EMST* [3].**

| $\gamma$ | $\beta$ | $H(\gamma,\beta)$ |
|---|---|---|
| $\gamma > 2$ | $\beta > 2$ | $\Theta(n)$ |
| | $\beta = 2$ | $\Theta(n \cdot \log n)$ |
| | $1 < \beta < 2$ | $\Theta(n^{2-\frac{\beta}{2}})$ |
| | $\beta = 1$ | $\Theta(\frac{n^{3/2}}{\sqrt{\log n}})$ |
| | $0 \le \beta < 1$ | $\Theta(n^{3/2})$ |
| $\gamma = 2$ | $\beta \ge 2$ | $\Theta(n \cdot \log n)$ |
| | $1 < \beta < 2$ | $\Theta(n^{2-\frac{\beta}{2}})$ |
| | $\beta = 1$ | $\Theta(\frac{n^{3/2}}{\sqrt{\log n}})$ |
| | $0 \le \beta < 1$ | $\Theta(n^{3/2})$ |
| $3/2 < \gamma < 2$ | $\beta \ge 2\gamma - 2$ | $\Theta(n^{3-\gamma})$ |
| | $1 < \beta < 2\gamma - 2$ | $\Theta(n^{2-\frac{\beta}{2}})$ |
| | $\beta = 1$ | $\Theta(\frac{n^{3/2}}{\sqrt{\log n}})$ |
| | $0 \le \beta < 1$ | $\Theta(n^{3/2})$ |
| $\gamma = 3/2$ | $\beta > 1$ | $\Theta(n^{3/2})$ |
| | $\beta = 1$ | $\Theta(n^{3/2} \cdot \sqrt{\log n})$ |
| | $0 \le \beta < 1$ | $\Theta(n^{3/2} \cdot \log n)$ |
| $1 < \gamma < 3/2$ | $\beta \ge 0$ | $\Theta(n^{3-\gamma})$ |
| $\gamma = 1$ | $\beta \ge 0$ | $\Theta(\frac{n^2}{\log n})$ |
| $0 \le \gamma < 1$ | $\beta \ge 0$ | $\Theta(n^2)$ |

Thus, we have

$$N_\mathcal{L} = \sum_{b=1}^{n}\sum_{a=1}^{q_i} l_{b,a} \cos \psi_{b,a} \ge H(\gamma, \beta).$$

Through using the results in Lemma 3 and Lemma 4, we obtain the upper bound for strong mobility case via the ad hoc way,

$$\lambda \le \frac{\sum_{i:X_i^h \in I_\mathcal{L}} \sum_{j:X_j^h \in E_\mathcal{L}} \mu_{ij}}{N_\mathcal{L}}$$
$$\le \frac{Wn^2 g(n) \int_{X\in I_\mathcal{L}} \int_{Y\in I_\mathcal{L}} \theta(\eta(n)\|X - Y\|) d_X d_Y}{H(\gamma, \beta)}.$$

Finally, we have

$$\lambda = O\left(\frac{Wn\pi c_1^2}{H(\gamma, \beta)\eta(n)}\right) = O\left(\frac{Wn}{H(\gamma, \beta)\eta(n)}\right).$$

□

#### 2) LOWER BOUND

In the strong mobility case, we divide the area of $\mathcal{O}$ into regular tessellations with the side length $\frac{c_2}{\eta(n)}$, where $c_2$ is a constant. The side length can satisfy the condition of Lemma 1 which guarantees that each tessellation has home points. The side length is equal to the mobile radius being of order $\Theta(\frac{1}{\eta(n)})$. This length drives nodes to meet each other with high probability in two adjacent tessellations under scheduling scheme $\mathcal{S}^\sharp$.

We introduce the *Manhattan Multicast Routing Tree* in literature [7], [28] as the routing policy. We adopt this policy to construct a social-broadcast tree in virtue of the home point of each mobile user. The home points of adjacent tessellations use scheduling scheme $\mathcal{S}^\sharp$ to make the associated nodes transmit data.

*Lemma 5: In the strong mobility case, the probability of a social-broadcast flow going through a given tessellation $A_{tes}$ is*

$$\min\left(\frac{\sqrt{2}c_2 H(\gamma,\beta)}{\eta(n)} + \frac{Q(\gamma)c_2^2}{\eta^2(n)}, 1\right).$$

*Proof:* Let $l$ denote the length of a social-broadcast flow. Then let this flow map into the horizontal and vertical projects, which are defined by $l_h$ and $l_v$, respectively. In the strong mobility case, the side length of $A_{tes}$ is defined as $\frac{c_2}{\eta(n)}$ above. Thus, we can derive the probability of this social-broadcast flow going through the $A_{tes}$ by $\Pr(l, A_{tes})$, having

$$\Pr(l, A_{tes}) = \frac{c_2^2}{\eta^2(n)}\left(\frac{l_h + l_v}{\frac{c_2}{\eta(n)}} + 1\right) = \frac{c_2(l_h + l_v)}{\eta(n)} + \frac{c_2^2}{\eta^2(n)}.$$

From above equation, we have

$$\frac{c_2(l_h + l_v)}{\eta(n)} \le \frac{\sqrt{2}c_2 l}{\eta(n)}.$$

Then, with all social-broadcast sessions, we have

$$\Pr^{all}(l, A_{tes}) \le \frac{\sqrt{2}c_2 \sum_{i=1}^{n} |EST(\mathcal{S}_i)|}{\eta(n)} + \frac{2\sum_{i=1}^{n} q_i c_2^2}{\eta^2(n)}.$$

Using Lemma 9 in literature [1], the length of EST (Euclidean Spanning Tree) satisfies

$$\sum_{i=1}^{n} |EST(\mathcal{S'}_i)| = O(H(\gamma, \beta)).$$

We can obtain the order of the number of all nodes' friends, denoted by $Q(\gamma)$, from the proof of Lemma 6 in literature [1], having

$$Q(\gamma) = \sum_{i=1}^{n} q_i = \begin{cases} \Theta(n), & \gamma > 2; \\ \Theta(n\log n), & \gamma = 2; \\ \Theta(n^{3-\gamma}), & 1 < \gamma < 2; \\ \Theta(n^2/\log n), & \gamma = 1; \\ \Theta(n^2), & 0 \le \gamma < 1. \end{cases}$$

Therefore, we can obtain

$$\Pr^{all}(l, A_{tes}) = \min\left(\frac{\sqrt{2}c_2 H(\gamma,\beta)}{\eta(n)} + \frac{Q(\gamma)c_2^2}{\eta^2(n)}, 1\right).$$

□

*Theorem 2: Given a network $\mathcal{O}$ consisting of n mobile ad hoc nodes, in strong mobility case, the lower bound of per-node social-broadcast capacity can be achieved using the scheduling scheme $\mathcal{S}^\sharp$ as follows,*

$$\lambda = \Omega\left(\frac{Wn}{H(\gamma,\beta)\eta(n) + Q(\gamma)}\right).$$

*Proof:* Assume $A_{tes}$ and $B_{tes}$ are adjacent tessellations. Let $\underline{N}_h(A_{tes})$ and $\underline{N}_h(B_{tes})$ represent the lower bound of the number of mobile users whose home points fall in $A_{tes}$ and $B_{tes}$, respectively.

Since $\tau(n) = o(\frac{1}{\eta(n)})$, through Lemma 1, we have $\underline{N}_h(A_{tes}) = \underline{N}_h(B_{tes}) = \frac{c_2^2 n}{4\eta^2(n)}$.

Thus, we have the feasible maximal traffic flow between two adjacent tessellations, which is denoted by

$$\mu^{\mathcal{S}^\sharp}(\overline{d}_{A_{tes},B_{tes}}) \cdot \underline{N}_h(A_{tes})\underline{N}_h(B_{tes}).$$

Since $\overline{d}_{A_{tes},B_{tes}} = \frac{\sqrt{5}c_2}{\eta(n)}$, using the results in Lemma 3, we have

$$\mu^{\mathcal{S}^\sharp}(\overline{d}_{A_{tes},B_{tes}}) = Wg(n)\theta(\sqrt{5}c_2) = W\pi c_1^2\frac{\eta^2(n)}{n}\theta(\sqrt{5}c_2).$$

From Lemma 5, we know that the maximal load is

$$O(\frac{\sqrt{2}c_2 H(\gamma,\beta)}{\eta(n)} + \frac{Q(\gamma)c_2^2}{\eta^2(n)}).$$

Then, we have the lower bound for strong mobility case via the ad hoc way,

$$\lambda \ge \frac{\sum_{A_{tes}\in I_{\mathcal{L}}} \sum_{B_{tes}\in E_{\mathcal{L}}} \mu^{\mathcal{S}^\sharp}(\overline{d}_{A_{tes},B_{tes}}) \cdot \underline{N}_h(A_{tes})\underline{N}_h(B_{tes})}{\frac{\sqrt{2}c_2 H(\gamma,\beta)}{\eta(n)} + \frac{Q(\gamma)c_2^2}{\eta^2(n)}}.$$

Finally, we can derive

$$\lambda = \Omega(\frac{Wn}{H(\gamma,\beta)\eta(n) + Q(\gamma)}).$$

□

### B. THE COMPARISON BETWEEN THE UPPER BOUND AND LOWER BOUND FOR STRONG MOBILITY CASE FROM AD HOC PERSPECITVE

From Theorem 1 and Theorem 2, we can see the difference between the upper and lower bound of per-node capacity in ad hoc way is $Q(\gamma)$ in the denominator. Here we compare the orders of $H(\gamma, \beta)\eta(n)$ and $Q(\gamma)$. By [3, Lemma 6], we give the comparison between them in TABLE 3.

TABLE 3 shows that $\Theta(H(\gamma, \beta)\eta(n)) = \Theta(H(\gamma, \beta)\eta(n) + Q(\gamma))$, which means that the upper and the lower bounds are of the same order. There is no gap in our results between the upper and the lower bounds for strong mobility case in ad hoc way. Thus, we derive a tight capacity bound in Theorem 3.

*Theorem 3: Given a network $\mathcal{O}$ consisting of n mobile ad hoc nodes, in strong mobility case, the per-node social-broadcast capacity can be achieved by*

$$\lambda = \Theta(\frac{Wn}{H(\gamma,\beta)\eta(n)}).$$

**TABLE 3.** Comparison between the upper and lower bounds for strong mobility case in ad hoc way.

| $\gamma$ | $\beta$ | $H(\gamma,\beta)\eta(n)$ | $Q(\gamma)$ |
|---|---|---|---|
| $\gamma > 2$ | $\beta > 2$ | $n\eta(n)$ | $n$ |
| | $\beta = 2$ | $n\eta(n)\log n$ | |
| | $1 < \beta < 2$ | $n^{2-\beta/2}\eta(n)$ | |
| | $\beta = 1$ | $\frac{n^{3/2}\eta(n)}{\sqrt{\log n}}$ | |
| | $0 \le \beta < 1$ | $n^{3/2}\eta(n)$ | |
| $\gamma = 2$ | $\beta \ge 2$ | $n\eta(n)\log n$ | $n\log n$ |
| | $1 < \beta < 2$ | $n^{2-\beta/2}\eta(n)$ | |
| | $\beta = 1$ | $\frac{n^{3/2}\eta(n)}{\sqrt{\log n}}$ | |
| | $0 \le \beta < 1$ | $n^{3/2}\eta(n)$ | |
| $3/2 < \gamma < 2$ | $\beta \ge 2\gamma - 2$ | $\eta(n)n^{3-\gamma}$ | $n^{3-\gamma}$ |
| | $1 < \beta < 2\gamma - 2$ | $n^{2-\beta/2}\eta(n)$ | |
| | $\beta = 1$ | $\frac{n^{3/2}\eta(n)}{\sqrt{\log n}}$ | |
| | $0 \le \beta < 1$ | $n^{3/2}\eta(n)$ | |
| $\gamma = 3/2$ | $\beta > 1$ | $n^{3/2}\eta(n)$ | |
| | $\beta = 1$ | $n^{3/2}\eta(n)\sqrt{\log n}$ | |
| | $0 \le \beta < 1$ | $n^{3/2}\log n\eta(n)$ | |
| $1 < \gamma < 3/2$ | $\beta \ge 0$ | $\eta(n)n^{3-\gamma}$ | |
| $\gamma = 1$ | $\beta \ge 0$ | $\frac{\eta(n)n^2}{\log n}$ | $\frac{n^2}{\log n}$ |
| $0 \le \gamma < 1$ | $\beta \ge 0$ | $n^2\eta(n)$ | $n^2$ |

We list the capacity results in TABLE 4. Based on TABLE 4, we find that the network capacity does not decrease monotonically as parameters $\gamma$ and $\beta$ increase. Some detailed analyses about the capacity results are provided in Section VII-B.

### C. SOCIAL-BROADCAST CAPACITY FOR STRONG MOBILITY CASE FROM CELLULAR PERSPECTIVE

#### 1) UPPER BOUND

The following analysis is divided into three parts. The first part considers the traffic flows from mobile users to base stations; the second part considers the flows among base stations, and the third part considers the flows from base stations to mobile users.

According to Lemma 2 on the Generalized Random Geometric Graph (GRGG), we define the capacity crossing $\mathcal{L}$ as

$$\mu_{\mathcal{L}} = \sum_{i \in I_{\mathcal{L}}} \sum_{j \in E_{\mathcal{L}}} \mu(d_{ij}),$$

where $\mu_{\mathcal{L}}$ depends on the mobile users' home points. The definition of $\mu_{\mathcal{L}}$ is an alternative of the link capacity among all nodes in Definition 1.

*Lemma 6: Given a network $\mathcal{O}$ consisting of $n$ mobile ad hoc nodes and $m$ base stations, considering the flows from mobile users to base stations in strong mobility case, the upper bound of per-node social-broadcast capacity can be achieved by*

$$\lambda = O(\frac{W_{up} \cdot m}{n}).$$

**TABLE 4.** Social-broadcast capacity for strong mobility case in ad hoc way.

| $\gamma$ | $\beta$ | $\lambda$ |
|---|---|---|
| $\gamma > 2$ | $\beta > 2$ | $\Theta\left(\frac{W}{\eta(n)}\right)$ |
| | $\beta = 2$ | $\Theta\left(\frac{W}{\eta(n)\log n}\right)$ |
| | $1 < \beta < 2$ | $\Theta\left(\frac{Wn^{\frac{\beta}{2}-1}}{\eta(n)}\right)$ |
| | $\beta = 1$ | $\Theta\left(\frac{W\sqrt{\log n}}{\eta(n)\sqrt{n}}\right)$ |
| | $0 \le \beta < 1$ | $\Theta\left(\frac{W}{\eta(n)\sqrt{n}}\right)$ |
| $\gamma = 2$ | $\beta \ge 2$ | $\Theta\left(\frac{W}{\eta(n)\log n}\right)$ |
| | $1 < \beta < 2$ | $\Theta\left(\frac{Wn^{\frac{\beta}{2}-1}}{\eta(n)}\right)$ |
| | $\beta = 1$ | $\Theta\left(\frac{W\sqrt{\log n}}{\eta(n)\sqrt{n}}\right)$ |
| | $0 \le \beta < 1$ | $\Theta\left(\frac{W}{\eta(n)\sqrt{n}}\right)$ |
| $3/2 < \gamma < 2$ | $\beta \ge 2\gamma - 2$ | $\Theta\left(\frac{Wn^{\gamma-2}}{\eta(n)}\right)$ |
| | $1 < \beta < 2\gamma - 2$ | $\Theta\left(\frac{Wn^{\frac{\beta}{2}-1}}{\eta(n)}\right)$ |
| | $\beta = 1$ | $\Theta\left(\frac{W\sqrt{\log n}}{\eta(n)\sqrt{n}}\right)$ |
| | $0 \le \beta < 1$ | $\Theta\left(\frac{W}{\eta(n)\sqrt{n}}\right)$ |
| $\gamma = 3/2$ | $\beta > 1$ | $\Theta\left(\frac{W}{\eta(n)\sqrt{n}}\right)$ |
| | $\beta = 1$ | $\Theta\left(\frac{W}{\eta(n)\sqrt{n}\log n}\right)$ |
| | $0 \le \beta < 1$ | $\Theta\left(\frac{W}{\eta(n)\log n\sqrt{n}}\right)$ |
| $1 < \gamma < 3/2$ | $\beta \ge 0$ | $\Theta\left(\frac{Wn^{\gamma-2}}{\eta(n)}\right)$ |
| $\gamma = 1$ | $\beta \ge 0$ | $\Theta\left(\frac{W\log n}{\eta(n)n}\right)$ |
| $0 \le \gamma < 1$ | $\beta \ge 0$ | $\Theta\left(\frac{W}{\eta(n)n}\right)$ |

The result is obvious due to the competition for the limited $m \cdot W_{up}$ bandwidth resource among $n$ mobile users.

*Lemma 7: Given a network $\mathcal{O}$ consisting of $n$ mobile ad hoc nodes and $m$ base stations, considering the flows among base stations in strong mobility case, the upper bound of per-node social-broadcast capacity can be achieved by*

$$\lambda = O(\frac{W_{base} \cdot m^2}{Q(\gamma)}).$$

*Proof:* Assume that $C_{tes}$ and $D_{tes}$ are adjacent tessellations. Let $\underline{N}_h(C_{tes})$ and $\underline{N}_h(D_{tes})$ represent the lower bound of the number of base stations whose home points fall in $C_{tes}$ and $D_{tes}$, respectively; and let $\overline{N}_h(C_{tes})$ and $\overline{N}_h(D_{tes})$ represent the upper bound of the number of base stations whose home points fall in $C_{tes}$ and $D_{tes}$, respectively.

According to Lemma 2, we have a similar conclusion for base stations:

$$\lambda \le \frac{\sum_{i:Y_i \in I_{\mathcal{L}}} \sum_{j:Y_j \in E_{\mathcal{L}}} \mu_{ij}}{\sum_{s:Y_s \in I_{\mathcal{L}}} \sum_{d:Y_d \in E_{\mathcal{L}}} \lambda_{sd}}.$$

Furthermore, we denote the numerator of above inequality as $\mu_Y$, having

$$\mu_Y \ge W_{base} \cdot \sum_{C_{tes} \in I_{\mathcal{L}}} \sum_{D_{tes} \in E_{\mathcal{L}}} \underline{N}_h(C_{tes}) \underline{N}_h(D_{tes}),$$

and

$$\mu_Y \leq W_{base} \cdot \sum_{C_{tes} \in I_{\mathcal{L}}} \sum_{D_{tes} \in E_{\mathcal{L}}} \overline{N}_h(C_{tes}) \overline{N}_h(D_{tes}).$$

The bandwidth among the base stations can be assumed to be a constant. By applying Lemma 1, we have

$$\mu_Y \geq W_{base} \cdot \frac{1}{16} m^2 (16+\zeta)^2 \sum_{C_{tes} \in I_{\mathcal{L}}} \sum_{D_{tes} \in E_{\mathcal{L}}} \tau(n)^4,$$

and

$$\mu_Y \leq W_{base} \cdot 16 m^2 (16+\zeta)^2 \sum_{C_{tes} \in I_{\mathcal{L}}} \sum_{D_{tes} \in E_{\mathcal{L}}} \tau(n)^4.$$

In strong mobility case, $\tau(n)^4 = o(1)$ is proportional to the tessellation size. Thus, we obtain

$$\mu_Y \sim W_{base} \cdot m^2.$$

Since the number of source-destination pairs crossing $\mathcal{L}$ is $\Theta(\sum_{i=1}^{n} q_i)$, i.e., $\Theta(Q(\gamma))$, we finally obtain

$$\lambda = O(\frac{W_{base} \cdot m^2}{Q(\gamma)}).$$

□

*Lemma 8: Given a network $\mathcal{O}$ consisting of n mobile ad hoc nodes and m base stations, considering the flows from base stations to mobile users in strong mobility case, the upper bound of per-node social-broadcast capacity can be achieved by*

$$\lambda = O(\frac{W_{down} \cdot m}{Q(\gamma)}).$$

Here the proof of Lemma 8 is similar to the proof of Lemma 7.

Combining Lemma 6, Lemma 7 and Lemma 8, we have the following Theorem 4.

*Theorem 4: Given a network $\mathcal{O}$ consisting of n mobile users and m base stations, in strong mobility case, the upper bound of per-node social-broadcast capacity can be achieved using the cellular routing method as follows:*

$$\lambda = O(\min(\frac{W_{up} \cdot m}{n}, \frac{W_{base} \cdot m^2}{Q(\gamma)}, \frac{W_{down} \cdot m}{Q(\gamma)})).$$

#### 2) LOWER BOUND

In this section, we present the cellular routing scheme and analyze the lower bound in the strong mobility case.

*Definition 3 (Cellular Routing): Cellular routing consists of three phases. In the first phase, a social-broadcast source node $v_i$ sends the packets to a base station. In the second phase, the packets are routed to the base stations whose tessellations contain the $q_i$ destinations. In the last phase, those base stations broadcast packets to the destinations in their tessellations.*

*Lemma 9 [6]: In strong mobility case, a traffic rate of $\Theta(\frac{W_{up} \cdot m}{n})$ can be sustained from any mobile user to base stations in phase I of cellular routing.*

*Lemma 10: In strong mobility case, a traffic rate of $\Theta(\frac{W_{base} \cdot m^2}{Q(\gamma)})$ can be sustained among base stations in the phase II of cellular routing.*

*Proof:* For phase II, the maximal traffic flowing between two tessellations $E_{tes}$ and $F_{tes}$ via base stations is bounded by $\lambda \cdot Q(\gamma)$. It can be sustained if no edge connecting base stations from the two tessellations is overloaded, i.e., satisfying

$$\frac{\lambda \cdot Q(\gamma)}{N_h(E_{tes}) N_h(F_{tes})} \sim \frac{\lambda \cdot Q(\gamma)}{m^2} \leq W_{base},$$

where $N_h(E_{tes})$ and $N_h(F_{tes})$ denote the number of base stations in the tessellation $E_{tes}$ and $F_{tes}$ respectively. Hence, $\lambda \leq \Theta(\frac{W_{base} \cdot m^2}{Q(\gamma)})$ is feasible in this phase. □

*Lemma 11 [6]: In strong mobility case, a traffic rate of $\Theta(\frac{W_{down} \cdot m}{Q(\gamma)})$ can be sustained from one base station to $q_i$ destinations (mobile users) in the phase III of cellular routing.*

Combining Lemma 9, Lemma 10 and Lemma 11, we have the following Theorem 5.

*Theorem 5: Given a network $\mathcal{O}$ consisting of n mobile users and m base stations, in strong mobility case, the lower bound of per-node social-broadcast capacity can be achieved using the cellular routing scheme as follows:*

$$\lambda = \Theta(\min(\frac{W_{up} \cdot m}{n}, \frac{W_{base} \cdot m^2}{Q(\gamma)}, \frac{W_{down} \cdot m}{Q(\gamma)})).$$

### D. SOCIAL-BROADCAST CAPACITY FOR STRONG MOBILITY CASE BY HYBRID ROUTING

Therefore, combining Theorem 1 and Theorem 4, we obtain the upper bound of per-node social-broadcast capacity for strong mobility case by hybrid routing in Theorem 6.

*Theorem 6: Given a network $\mathcal{O}$ consisting of n mobile users and m base stations, in strong mobility case, the upper bound of per-node social-broadcast capacity can be achieved by the hybrid routing way as follows:*

$$\lambda = O\{\max[\frac{Wn}{H(\gamma,\beta)\eta(n)}, \min(\frac{W_{up} \cdot m}{n}, \frac{W_{base} \cdot m^2}{Q(\gamma)}, \frac{W_{down} \cdot m}{Q(\gamma)})]\}.$$

Then, combining the Theorem 2, Theorem 3 and Theorem 5, we obtain the lower bound of per-node social-broadcast capacity for strong mobility case by hybrid routing in Theorem 7.

*Theorem 7: Given a network $\mathcal{O}$ consisting of n mobile users and m base stations, in strong mobility case, the lower bound of per-node social-broadcast capacity can be achieved by the hybrid routing way as follows:*

$$\lambda = \Omega\{\max[\frac{Wn}{H(\gamma,\beta)\eta(n)}, \min(\frac{W_{up} \cdot m}{n}, \frac{W_{base} \cdot m^2}{Q(\gamma)}, \frac{W_{down} \cdot m}{Q(\gamma)})]\}.$$

Finally, through above Theorem 6 and Theorem 7, we have the social-broadcast capacity for strong mobility case with hybrid routing in Theorem 8.

*Theorem 8: Given a network $\mathcal{O}$ consisting of n mobile users and m base stations, in strong mobility case, the per-node social-broadcast capacity can be achieved by the hybrid routing way as follows:*

$$\lambda = \Theta\{\max[\frac{Wn}{H(\gamma,\beta)\eta(n)}, \min(\frac{W_{up}\cdot m}{n}, \frac{W_{base}\cdot m^2}{Q(\gamma)}, \frac{W_{down}\cdot m}{Q(\gamma)})]\}.$$

## VI. SOCIAL-BROADCAST CAPACITY FOR WEAK MOBILITY CASE

In this section, we discuss the weak mobility case under the condition $\tau(n) = \omega\left(\frac{1}{\eta(n)}\right)$. In this case, first we present a social-broadcast capacity bound for weak mobility case from the ad hoc perspective (**Theorem 9**); second, we introduce some studies related to the capacity bound for weak mobility case from cellular perspective and note the differences with our results.

### A. SOCIAL-BROADCAST CAPACITY FOR WEAK MOBILITY CASE FROM AD HOC PERSPECTIVE

Under the weak mobility case, node mobility does not play an important role in increasing the capacity. We can regard this case as an approximately static state. We choose $R_T = \Theta(\tau(n))$ to guarantee the network connectivity.

*Definition 4:* ***Scheduling Scheme*** $\mathcal{S}^\flat$

*We use $K^2$-TDMA scheduling scheme based on a tessellation partition with side length $\sqrt{(16+\zeta)}\tau(n)$, where $\zeta$ is a small constant, $\zeta > 0$.*

A previous study [7] shows that a constant $K$ that guarantees the successful scheduling of each tessellation in $K^2$ time-slots can be identified.

*Lemma 12: In the weak mobility case, the probability of a social-broadcast flow going through a given tessellation $A_{tes}$ is*

$$\min\left(\sqrt{2}H(\gamma,\beta)\sqrt{(16+\zeta)}\tau(n) + Q(\gamma)(16+\zeta)\tau^2(n), 1\right).$$

*Proof:* This proof is similar to the proof of Lemma 5. We know that the side length of the tessellation partition in weak mobility case is $\sqrt{(16+\zeta)}\tau(n)$. We use $\sqrt{(16+\zeta)}\tau(n)$ to replace the side length of $A_{tes}$ in the proof of Lemma 5. Then, we can complete this proof and obtain the result of Lemma 12. □

*Theorem 9: Given a network $\mathcal{O}$ consisting of n mobile ad hoc nodes, in weak mobility case, the lower bound of per-node social-broadcast capacity can be achieved through scheduling scheme $\mathcal{S}^\flat$ as follows:*

$$\lambda = \Omega\left(\frac{W}{H(\gamma,\beta)\sqrt{\frac{\log n}{n}}}\right).$$

*Proof:* Similarly, we suppose that there are two adjacent tessellations $A_{tes}$ and $B_{tes}$. In the scheduling scheme $\mathcal{S}^\flat$, the maximum feasible traffic flow is of order $\frac{W}{K^2}$.

Using Lemma 12, we obtain the maximal number of social-broadcast flows,

$$O(\sqrt{2}H(\gamma,\beta)\sqrt{(16+\zeta)}\tau(n) + Q(\gamma)(16+\zeta)\tau^2(n)).$$

Thus, we obtain the lower bound for weak mobility case in ad hoc way,

$$\lambda \geq \frac{\frac{W}{K^2}}{\sqrt{2}H(\gamma,\beta)\sqrt{(16+\zeta)}\tau(n) + Q(\gamma)(16+\zeta)\tau^2(n)}.$$

Finally, we obtain

$$\lambda = \Theta\left(\frac{W}{H(\gamma,\beta)\sqrt{\frac{\log n}{n}} + Q(\gamma)\frac{\log n}{n}}\right).$$

Further, we compare the order of the two factor $H(\gamma,\beta)\sqrt{\frac{\log n}{n}}$ and $Q(\gamma)\frac{\log n}{n}$ in the denominator. Also, through the derivation based on TABLE 3, we found that the order of the former is larger than that of the latter. Therefore, we have

$$\lambda = \Theta\left(\frac{W}{H(\gamma,\beta)\sqrt{\frac{\log n}{n}}}\right).$$

□

Our results are listed in TABLE 5. Through analyzing the results in Section V-A and Section VI-A, we find that the strong mobility case has an obviously larger capacity than the weak mobility case. This finding is consistent with the well-known conclusion that mobility can increase the capacity [11].

### B. SOCIAL-BROADCAST CAPACITY FOR WEAK MOBILITY CASE FROM CELLULAR PERSPECTIVE

The weak mobility case can be considered a static case. Using the cellular method, a larger network capacity can be achieved compared with the use of the ad hoc way. Since previous studies [18], [19] have already discussed the capacity of a static network with base stations, we refer to these studies for details.

The difference between these previous results and ours is the number of sessions in the network. In those studies, the number of sessions is order of $n$, whereas in our study, it is order of $Q(\gamma)$.

## VII. EVALUATION

### A. HETEROGENEOUS MOBILITY

In the paper, our mobility model is a home point based model, and the moving of users is heterogeneous, which is reflected in two aspects. First, many users gather in some regions and form different groups. Second, the user often moves around a center/home point in an area with high probability.

Here, we use two check-in datasets, Gowalla and Brightkite [29], to show the reality of the heterogeneous mobility. Both of the datasets come from the location based social networking service provider in which users share their locations by checking-in. The datasets are published in SNAP [30]. Gowalla contains a total of 6,442,890 check-ins of 196,591 users over the period of Feb.2009-Oct.2010. Brightkite contains a total of 4,491,143 check-ins of 58,228 users over the period of Apr.2008-Oct.2010.

**TABLE 5.** **Social-broadcast capacity for weak mobility case in ad hoc way.**

| $\gamma$ | $\beta$ | $\lambda$ |
|---|---|---|
| $\gamma > 2$ | $\beta > 2$ | $\Theta\left(\frac{W}{\sqrt{n\log n}}\right)$ |
| | $\beta = 2$ | $\Theta\left(\frac{W}{\log n\sqrt{n\log n}}\right)$ |
| | $1 < \beta < 2$ | $\Theta\left(\frac{Wn^{\frac{\beta}{2}-1}}{\sqrt{n\log n}}\right)$ |
| | $\beta = 1$ | $\Theta\left(\frac{W}{n}\right)$ |
| | $0 \le \beta < 1$ | $\Theta\left(\frac{W}{n\sqrt{\log n}}\right)$ |
| $\gamma = 2$ | $\beta \ge 2$ | $\Theta\left(\frac{W}{\log n\sqrt{n\log n}}\right)$ |
| | $1 < \beta < 2$ | $\Theta\left(\frac{Wn^{\frac{\beta}{2}-1}}{\sqrt{n\log n}}\right)$ |
| | $\beta = 1$ | $\Theta\left(\frac{W}{n}\right)$ |
| | $0 \le \beta < 1$ | $\Theta\left(\frac{W}{n\sqrt{\log n}}\right)$ |
| $3/2 < \gamma < 2$ | $\beta \ge 2\gamma - 2$ | $\Theta\left(\frac{Wn^{\gamma-5/2}}{\sqrt{\log n}}\right)$ |
| | $1 < \beta < 2\gamma - 2$ | $\Theta\left(\frac{Wn^{\frac{\beta}{2}-1}}{\sqrt{n\log n}}\right)$ |
| | $\beta = 1$ | $\Theta\left(\frac{W}{n}\right)$ |
| | $0 \le \beta < 1$ | $\Theta\left(\frac{W}{n\sqrt{\log n}}\right)$ |
| $\gamma = 3/2$ | $\beta > 1$ | $\Theta\left(\frac{W}{n\sqrt{\log n}}\right)$ |
| | $\beta = 1$ | $\Theta\left(\frac{W}{n\log n}\right)$ |
| | $0 \le \beta < 1$ | $\Theta\left(\frac{W}{n\log^{3/2} n}\right)$ |
| $1 < \gamma < 3/2$ | $\beta \ge 0$ | $\Theta\left(\frac{Wn^{\gamma-5/2}}{\sqrt{\log n}}\right)$ |
| $\gamma = 1$ | $\beta \ge 0$ | $\Theta\left(\frac{W}{n\sqrt{n/\log n}}\right)$ |
| $0 \le \gamma < 1$ | $\beta \ge 0$ | $\Theta\left(\frac{W}{n\sqrt{n\log n}}\right)$ |

We count the check-ins of all users in the U.S. area. Fig. 5 shows that the distribution of location check-ins is heterogeneous. The check-ins in some areas are dense, which demonstrates that users are prone to form clusters in these dense areas.

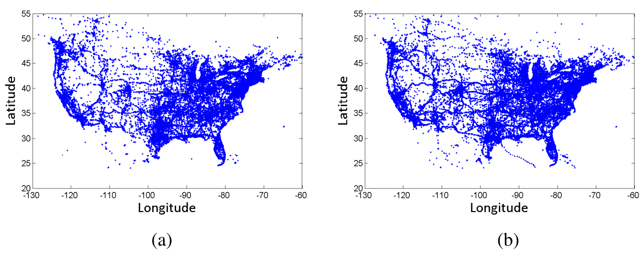



**FIGURE 5.** **Distribution of check-ins in the U.S. (a) Gowalla Dataset. (b) Brightkite Dataset.**

Next, from the above two datasets, we randomly capture the check-ins of three users. In Fig. 6, three different colors (red, blue and green) represent the different users. We find that a moving user checks in from a fixed location often. The fixed location can be considered as the home point of this user. It demonstrates that the home point based phenomenon exists in the real world.

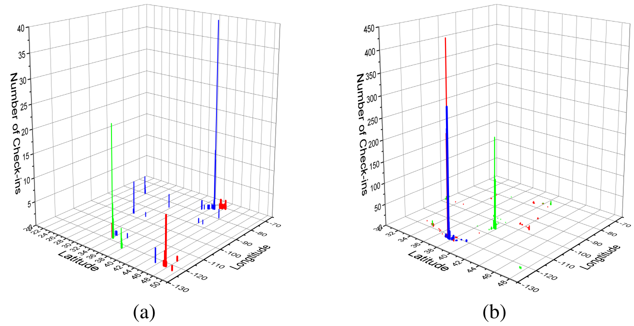



**FIGURE 6.** **Check-ins statistics for three different users. (a) Gowalla Dataset. (b) Brightkite Dataset.**

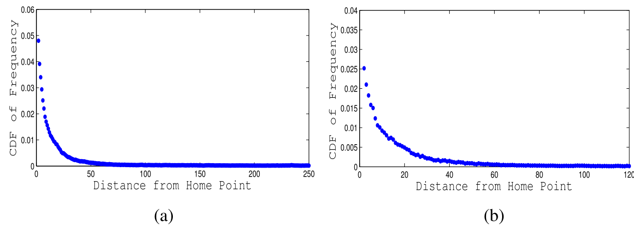



**FIGURE 7.** **Relationship between the check-in frequency and the distance from the home point. (a) Gowalla Dataset. (b) Brightkite Dataset.**

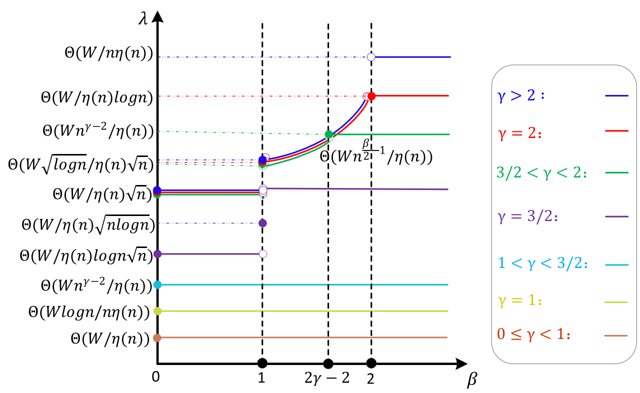
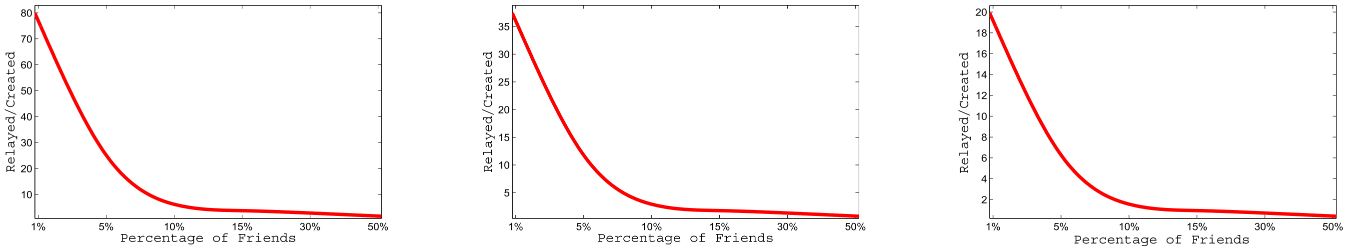



**FIGURE 8.** **Illustration of the piecewise functions for social-broadcast capacity in strong mobility case using ad hoc way.**

Finally, we show the relationship between distance and check-ins. In both datasets, we choose the location of each user with maximum check-ins as the home point. Fig. 7 shows that the farther the user moves away from its home point, the lower the check-in frequency is. This finding demonstrates that most users move around their home points with high probability.

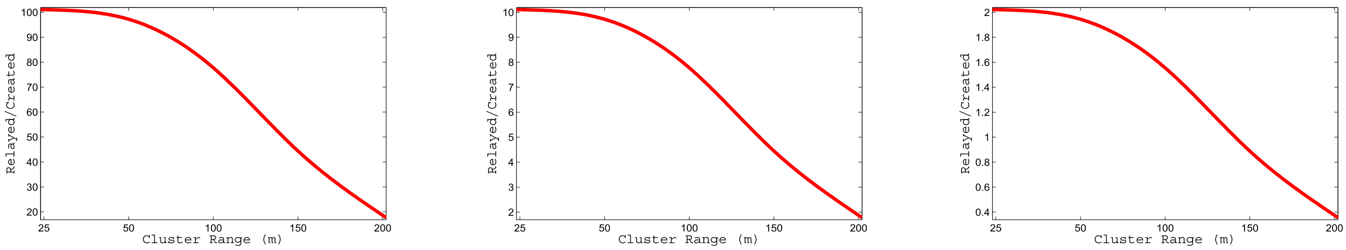
## B. THEORETICAL RESULTS ANALYSIS AND VALIDATION

In Section V and Section VI, we give the data transport capacity results of mobile networks for mobile social services. *With the infrastructure support, the subtle differences of the theoretical results are affected by the clustering exponent of friendship degree $\gamma$ and friendship formation $\beta$.*




(a) (b) (c)

**FIGURE 9.** **Relationship between the network capacity and the number of friends. (a) Cluster Range = 100. (b) Cluster Range = 150. (c) Cluster Range = 200.**




(a) (b) (c)

**FIGURE 10.** **Relationship between the network capacity and the cluster range. (a) Percentage of Friends = 1%. (b) Percentage of Friends = 10%. (c) Percentage of Friends = 50%.**

An illustration of the piecewise capacity $\lambda$ in TABLE 4 is shown in Fig. 8. Here, we take the results in TABLE 4 as an example and give intuitive explanations as follows:

1) When the clustering exponent of friendship degree $\gamma$ is bigger, the number of friends of each user is limited by a smaller upper bound with high probability. It possibly reduces the interference among nodes and increases the social-broadcast capacity.
2) When the clustering exponent of friendship formation $\beta$ is bigger, the friends may be closer to each user with high probability. It possibly reduces the total transmission distance of each social-broadcast session. The nodes can deliver messages directly to other nodes without moving far away. It ultimately results in a larger social-broadcast capacity. Shortly speaking, the bigger parameters $\gamma$ and $\beta$ are, the larger social-broadcast capacity is.

Thus, the piecewise capacity results are significantly affected by the parameters $\gamma$ and $\beta$. Next, we validate the relationship between the capacity and the two parameters.

We use 'The ONE' simulator [31] to emulate the network capacity. This simulator can observe the entire data transportation process in the network. We emulate 1000 moving nodes in a $200m \times 200m$ square area. The transmission range is $2.5m$. We partition the nodes into 10 clusters and cast the 10 clusters randomly in the network area. The size of each cluster is 100. To emulate the social characteristics, we have settings as follows.

1) The social movements show the phenomenon of restricted mobility. By changing the cluster diameter through the range $100m$ to $150m$ to $200m$, we allowed the nodes in each cluster to move around the entire network.
2) The parameter $\gamma$ fixes the number of friends for each user. In the simulation, we realize this parameter by setting the number of destinations/friends for each source. We let each node choose its friends in the network randomly. The parameter $\beta$ fixes the distance between each source and its destinations/friends. In the simulation, we realize the parameter $\beta$ by controlling the size of the cluster range.
3) The clusters are overlapped with each other. Since the transmission range is $2.5m$, the relay nodes between the source-destination can be chosen in any clusters within the transmission range.
4) Since we discuss the social broadcast capacity, we execute epidemic routing among the source and its friends. Additionally, we use the ratio of 'relayed packets' to 'created packets' to reflect the network capacity.

Note that, although we cannot totally emulate the social traces of users, the above settings can model friendships, distances of friendships, social broadcasts, and restricted mobility. These settings are sufficient to study the relationship between capacity and the two parameters $\gamma$ and $\beta$.

Next, we perform the simulation to test the variation of the network capacity with the parameters $\gamma$ and $\beta$ so as to validate the correctness of the capacity results derived in the paper.

With a fixed cluster range, we change the number of friends of a user to observe the variation of the network capacity, shown in Fig. 9. The number of friends of a user equals the percentage of friends of a user multiplied by the size of the cluster. A large percentage of friends means that the number of destinations/friends of a user is large, i.e., the parameter $\gamma$ is small. We perform the simulation in different scenarios (cluster range $= 100, 150, 200$). From Fig. 9 (a)-(c), we observe that the smaller the number of friends is, the larger the value of 'relayed packets/created packets' is. This demonstrates that a larger parameter $\gamma$ limits the number of friends, which reduces the interference of simultaneous transmissions and results in a large network capacity.

Next, with a fixed number of friends, we change the cluster range to observe the variation of the network capacity, shown in Fig. 10. A large cluster range means the moving range of the node is large. If the distance between the friends and its source is large, the parameter $\beta$ is small. We perform the simulation in different scenarios (the percentage of friends for a user $= 1\%, 10\%, 50\%$). From Fig. 10 (a)-(c), we see that the smaller the cluster range is, the larger the value of 'relayed packets/created packets' is. This finding demonstrates that a larger parameter $\beta$ limits the transmission distance between the source and its destinations, which results in a large network capacity.

## VIII. CONCLUSION

In this paper, we mainly study the capacity of mobile networks for mobile social services under the hybrid communication architecture. We construct a system model by introducing a three-layered social network model. We use the clustered model to characterize the spatial inhomogeneities of node density in the physical layer. Then, through an improved population-based model, we successfully address social relationship formation in the mobile environment and obtain the degree distribution of mobile users' friends. Finally, we derive the results of the network capacity of social-broadcast. This work can serve as the first step in investigating the capacity of mobile ad hoc social networks (MAHSNs) with infrastructure support. Besides, we consider that each user has only one home point in the paper. In reality, a person may have many high activity locations. In the future, we can extend the one home point based model to a general case of multi-center model, i.e., having more than one home point.

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