OPTIMUM TRANSMIT RANGE AND CAPACITY OF MOBILE INFOSTATION NETWORKS

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Abstract — **A mobile infostation network stipulates all transmissions to occur when nodes are in proximity. In this paper, the effect of transmit range on the capacity of four transmission strategies is studied. We show that a stipulated transmit range improves the capacity compared to the Grossglauser-Tse strategy with an unconstrained transmit range by 25%, and outperforms the non rate-adaptive strategy by 68%. This indicates an optimal trade-off exists between spatial transmission concurrency and spectral efficiency on individual links. The optimal number of neighbors is invariant to node density, and is between 0.6 to 1.2 for our transmission strategies. This should be contrasted to a magic number of 6 to 8 neighbors for multihop networks, where the expected forward progress per hop is maximized. This reflects the different optimization criteria of mobile infostation and multihop ad hoc networks. In addition, the capacity per unit area increases linearly with node density. This is counter-intuitive but can be explained using a rescaling argument drawn from percolation theory.**

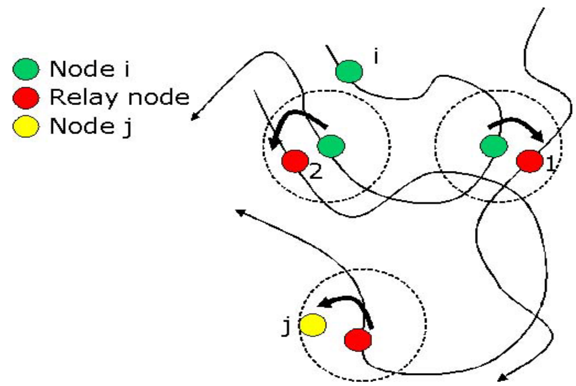

Fig. 1. Two hop packet relay strategy in a mobile infostation network.

I. INTRODUCTION

In a mobile infostation network, nodes operate on low transmit power. Any two nodes communicate only when they are in proximity and have a very good channel. Under this transmission constraint, any pair of nodes is intermittently connected as mobility shuffles the node locations. The network capacity of mobile infostation networks compares favorably to multihop ad hoc networks. In [2] Gupta and Kumar showed that the per node throughput in a multihop network drops to zero at a rate $O(\frac{1}{\sqrt{n \ln n}})$ in the limit of large number of nodes n. Thus multihop networks do not always scale with large network size. On the other hand, Grossglauser and Tse showed in [1] that the per node throughput of mobile infostation networks is $O(1)$, independent of the number of nodes. This capacity is achieved through a two hop relay strategy.

Assume that each node in the network selects a random destination for unicast. We focus on a source node i, which has packets to deliver to a destination node j, as shown in Figure 1. As time evolves, node i moves along a random trajectory and eventually encounters nodes 1 and 2. Although neither nodes 1 nor 2 are the destination of i, i still relays packets to them, with the expectation that when each of these relay nodes reaches the destination j, it will complete the second relay on behalf of node i. In steady state, each of the other $n-2$ nodes contains packets generated by node i and destined to node j. At any network snapshot, it is almost surely that the nearest neighbor of node j has packets addressed from node i and completes the second relay on the behalf of i. That is, the long run per node throughput is constant and is independent of the network size. This capacity improvement comes from the exploitation of node mobility to physically carry the packets around the network, and is independent of the underlying mobility model, as long as the mobility process is ergodic.

Motivated by the dramatic capacity improvement of mobile infostation networks, there are a number of recent papers on ad hoc networks that exploit node mobility. Whereas [1] focused on unicast, most other papers focused on multicast. [8, 9] has focused on scenarios in which nodes cooperate. In order to expedite data dissemination, a node also forwards packets for other nodes if it has not done so for some time. The issue of noncooperation between nodes was explored in [14, 15] in the context of a content distribution application. Transmissions between two proximate nodes are allowed only when both nodes benefit from a file exchange. On the other hand, the effect of node mobility on highway mobile infostation networks is examined in [16, 17]. The achievable data rate of a node is shown to improve with its speed.

In the mobile infostation literature, the concept of physical proximity is not well characterized. In [7, 14], it is assumed that the planar network consists of discrete locations, in which any two collocated nodes can participate a file exchange. Physical proximity is defined in terms of a hypothetical grid of discrete points, leading to an overly simplified mobility and interference model. On the other hand, [1] assumed that a *candidate transmit node* always transmits to the closest receive node. Although the transmit and receive node pair has the shortest distance, this strategy may not perform well since this distance may be large in some topology realizations. In these links, the benefit of spatial transmission concurrency may be more than offset by a simultaneous increase in total interference power in the network. It may be worthwhile to suppress packet transmissions when the channel is less than excellent to the receive node closest in distance. The resultant decrease in total interference power due to the suppression of these transmissions may be beneficial to the sum rate of the remaining connections. To ensure that only excellent channels are used, a natural strategy will be to impose an artificial *transmit range* for all nodes. A transmit node may well see many receive nodes beyond the transmit range due to the physical proximity of nodes. However, we impose this artificial transmit range and block all these potential transmissions. Here

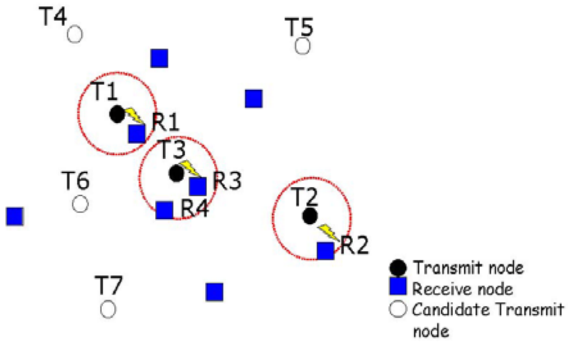

Fig. 2. A network populated with candidate transmit nodes and receive nodes. A candidate transmit node attempts a transmission if there are receive nodes in its transmit range.

we explicitly trade spatial transmission concurrency for greater spectral efficiency of the remaining connections in the network. As far as the transmit node is concerned, all nodes within the transmit range are its *neighbors*. It is desirable to see if the stipulation of an artificial transmit range will further improve the network capacity.

The rest of the paper is organized as follows. In section II, we describe the system model, the four strategies and the performance metric. In section III-A, four transmission strategies are compared on the basis of capacity maximization. We identify the scaling invariance property of the network in section III-B and compare the optimal parameters of the four transmission strategies in section III-C. Finally, we discuss the implications of our results and wrap up in section IV.

II. System Model

We assume nodes populate a planar region according to a homogeneous spatial Poisson process with node densityλ. Time is divided into slots. In each slot, a fraction θ of all mobile nodes are randomly selected as *candidate transmit nodes* such that the candidate transmit and receive nodes have spatial Poisson distributions with average node density $\lambda\theta$ and $\lambda(1-\theta)$ respectively [4].

We consider a sender-centric transmission model for the nodes. A candidate transmit node transmits when there are receive nodes within a ring of radius r_0. Referring to the example of Figure 2, three transmit nodes (T1 to T3) have receive nodes in their transmit range and therefore proceed with transmission. The remaining candidate transmit nodes (T4 to T7) cannot find any receive node and remain silent in the time slot. If there are more than one receive node in range, say T3, it may select a receive node randomly, or the closest receive node in range R3, and initiate data transmission. It may happen that two transmit nodes select the same receive node simultaneously, which is not a problem for receivers that can capture more than one packet.

We assume all nodes transmit at the same power. The network is interference limited and background noise at a receive node is neglected. In this case, the SIR at a receive node is independent of the transmit power, which is normalized to 1. The path gain $g(r)$ of a signal is solely determined by the distance r between a transmitter and receiver. Second order effects such as shadowing and multipath fading [12] are ignored. We assume that interference combines non-coherently at each receive node and treat the total interference power as the sum of the interference power of a Poisson field of interferers. Denoting the distance of node i to its intended receive node j as r_{ij}, the SIR at the receive node j is thus

$$\gamma_j = \frac{g(r_{ij})}{Y} = \frac{g(r_{ij})}{\sum_{k\neq i} g(r_{kj})} \quad (1)$$

where Y is the summation of interference power contributions from all interference transmitters. Moreover, each point in the plane sees the same interference statistics due to the spatial invariance of homogeneous Poisson process. The subscript j in the SIR γ is dropped in subsequent analysis to emphasize the spatial invariance of SIR.

Assume our systems operate on unit bandwidth. The transmission strategies described in this paper are compared in the metric of *expected capacity per unit area* $E[C]$, in the unit $bit/s/m^2$. Here the notion of capacity is defined in a loose sense. The theoretical capacity of the strategies are computed under the assumption of single-user receiver decoding. The capacity represents an upper bound performance of a particular transmission and reception strategy and should not be confused with the maximum network capacity over all possible networking and decoding strategies. Mathematically, the capacity per unit area is written as

$$E[C] = E[\lambda_t \log_2(1 + g(R)/Y)] \quad (2)$$

where λ_t is the node density of the transmit nodes, and $\log_2(1+g(R)/Y)$ is the link capacity at SIR $g(R)/Y$. The expectation is taken over the random variables R the communication distance of the node pair and total interference power Y. Our aim is to determine the optimum transmit range r_0 and the fraction of candidate transmit nodes θ based on the objective $E[C]$.

We investigate four transmission strategies in this paper: a non rate-adaptive strategy, a random node in range strategy, a closest node in range strategy and the closest node strategy. In the non rate-adaptive strategy, the transmission rate is constant and determined by the SIR at the transmit range boundary, $\gamma(r_0) = g(r_0)/Y$. Even if the SIR is higher when two nodes are closer than distance r_0, the additional link capacity warranted by the higher SIR is not exploited. We denote the performance metric of the non rate-adaptive strategy as $E[\underline{C}]$ to allude that this strategy provides a lower performance bound to the four strategies.

Both the random node in range and the closest node in range strategies operate on the assumption of adaptive transmission. In the random node in range strategy, a candidate transmit node randomly selects a receive node when multiple receive nodes are within its range. In the closest node in range strategy, the closest node in range is selected to exploit the best channel. In the case there are no receive nodes in the range of a candidate transmit node, as are all the transparent nodes in Figure 2, no transmission is scheduled. It is obvious the latter strategy has superior performance since the candidate transmit node always selects the receive node with the best SIR and link capacity. We denote the performance metric as $E[\overline{C}]$ to emphasize that this strategy provides an upper performance bound of all the four strategies. The corresponding metric for the random node in range strategy is denoted as $E[C_{rand}]$.

We also examine a reference strategy with an unconstrained transmit range, where a candidate transmit node always transmits to the closest receive node. This strategy is similar to the strategy in [1], though there is no consideration of rate adaptation in that paper. For the sake of comparison, however, we assume the reference strategy is rate-adaptive. Hereafter, we refer to this strategy as the Grossglauser-Tse (GT) strategy. The corresponding capacity per unit area is denoted as $E[C_{GT}]$. Since there is no transmit range for this strategy, we optimize $E[C_{GT}]$ over θ.

In order to compute $E[C]$, we need to derive the PDF of the total interference power Y and connection distance R of the node pair. We employ the two ray ground reflection model [10]; the path gain is given by $g(r) = r^{-4}$. Our derivation of the interference statistics closely parallels that in [11], with node density λ replaced by the transmit node density λ_t to denote the point process of the transmit nodes. Suppose the transmit range of all nodes is r_0. A candidate transmit node transmits if the number of receive nodes in its range $N(r_0)$ is non zero. Thus, the transmit node density λ_t is

$$\lambda_t = \lambda\theta Pr[N(r_0) > 0] = \lambda\theta(1 - e^{-\lambda(1-\theta)\pi r_0^2}). \quad (3)$$

Following the same steps in [11], the PDF $f_Y(y)$ can be derived and is dependent on the transmit node density only, given by

$$f_Y(y) \;=\; \frac{\pi}{2}\lambda_t y^{-3/2} e^{-\pi^3\lambda_t^2/4y}. \quad (4)$$

III. Performance Analysis

A. Capacity Maximization

In the non rate-adaptive strategy, the SIR γ is a function of random interference power only. The expected capacity per unit area is therefore obtained by conditioning on the total interference power Y.

$$\begin{aligned} E[\underline{C}] &= E[\lambda_t \log_2(1+\underline{\gamma})] \\ &= \frac{\lambda_t}{\ln 2}\int_0^\infty \ln\Big(1+\frac{g(r_0)}{y}\Big) f_Y(y)dy \\ &= -\frac{\lambda_t}{\ln 2}\Bigg(\frac{\pi^3\lambda_t^2 r_0^4}{2}\ {}_2F_2\Big(1,1;\frac{3}{2},2;\frac{\pi^3 r_0^4\lambda_t^2}{4}\Big) \\ &\quad + b - \pi\ \mathrm{erfi}\Big(\frac{\pi^{3/2} r_0^2\lambda_t}{2}\Big) + \ln(\pi^3 r_0^4\lambda_t^2)\Bigg) \end{aligned} \quad (5)$$

where

$$b = \lim_{n\to\infty}\Big(\sum_{k=1}^{n}\frac{1}{k} - \ln n\Big) \approx 0.5772 \quad (6)$$

is Euler's constant and $\mathrm{erfi}(x)$ is the imaginary error function given by

$$\mathrm{erfi}(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{t^2}dt. \quad (7)$$

In addition, ${}_pF_q(a_1,...,a_p;b_1,...,b_q;x)$ is the generalized Hypergeometric function, a series of the form

$${}_pF_q(a_1,...,a_p;b_1,...,b_q;x) = \sum_{k=0}^{\infty} c_k x^k, \quad (8)$$

for which $c_0 = 1$ and the ratio of successive terms is

$$\frac{c_{k+1}}{c_k} \;=\; \frac{(k+a_1)(k+a_2)...(k+a_p)}{(k+b_1)(k+b_2)...(k+b_q)(k+1)}. \quad (9)$$

We observe that both the generalized Hypergeometric function and the imaginary error function diverge as x increases. However, the difference of these two functions is always finite.

When the transmission strategy is rate-adaptive, the expected capacity per unit area is obtained by conditioning on both the interference power and communication distance. Given there exists a non-zero number of nodes $N(r_0)$ in the coverage radius, we define R as the distance to the receive node to which we communicate. We denote the PDF of the connection distance R as $f_R(r|n)$. It is implicitly understood that the number of receive nodes in the transmit range $N(r_0)$ is non zero when a transmission is attempted. On the other hand, the PDF may be dependent on the number of receive node n in the transmit range.

Since the receive nodes are Poisson distributed with intensity

$$\lambda_r = \lambda(1-\theta), \quad (10)$$

each receive node within the range is uniformly located in the area πr_0^2. In the random node in range strategy, the distance between the random receive node and the transmit node therefore has a PDF

$$f_R(r) = \begin{cases} 2r/r_0^2 & 0 \le r \le r_0 \\ 0 & \text{o.w.} \end{cases} \quad (11)$$

independent of n. For the closest node in range strategy, the distance is the minimum of among the receive node distances. Given $N(r_0) = n$ receive nodes in range, it is straightforward to deduce

$$f_{R|N(r_0)}(r|n) = \frac{2nr}{r_0^2}\left(1 - \left(\frac{r}{r_0}\right)^2\right)^{n-1}. \quad (12)$$

The PDF of the distance to the closest receive node is then computed by averaging over $N(r_0)$:

$$\begin{aligned} f_R(r) &= \sum_{n=1}^{\infty} f_{R|N(r_0)}(r|n) Pr[N(r_0) = n] \\ &= \frac{2\lambda_r \pi r e^{-\lambda_r\pi r^2}}{1 - e^{-\pi\lambda_r r_0^2}} \qquad 0 \le r \le r_0. \end{aligned} \quad (13)$$

In the GT strategy, a candidate transmit node always transmits. Taking the limit $r_0 \to \infty$ in (13), the PDF of the connection distance $f_R(r)$ with an unconstrained transmit range is

$$f_R(r) = 2\pi r\lambda_r e^{-\lambda_r\pi r^2} \qquad 0 \le r < \infty. \quad (14)$$

For the above adaptive strategies, the expected sum rate per unit area $E[C]$ is then computed as

$$\begin{aligned} & E[E[\lambda_t \log_2(1+\gamma(R,Y))]] \\ =\; & \frac{\lambda_t}{\ln 2}\int_0^{r_0}\int_0^\infty \ln\Big(1+\frac{g(r)}{y}\Big) f_Y(y)dy f_R(r)dr \end{aligned} \quad (15)$$

where $f_R(r)$ assumes the form of (11), (13), (14) for the three rate-adaptive strategies. In the random node in range strategy, $E[C_{rand}]$ can be evaluated as

$$\begin{aligned} & \frac{1}{2r_0^2\ln 2}\Bigg[2\pi r_0^2\lambda_t \mathrm{erfi}\Big(\frac{\pi^{3/2} r_0^2\lambda_t^2}{2}\Big) - \frac{\pi^3 r_0^6\lambda_t^3}{3}\ {}_2F_2\Big(1,1;2,\frac{5}{2};\frac{\pi^3 r_0^4\lambda_t^2}{4}\Big) \\ & -\frac{2}{\pi}\Big(-2(1-e^{\frac{\pi^3 r_0^4\lambda_t^2}{4}} + \pi r_0^2\lambda(b-2) + \lambda_t\pi r_0^2\ln(\pi^3 r_0^4\lambda_t^2)\Big)\Bigg]. \end{aligned} \quad (16)$$

For the closest node within range and the GT strategy, (15) cannot be evaluated analytically and numerical integration must be used.

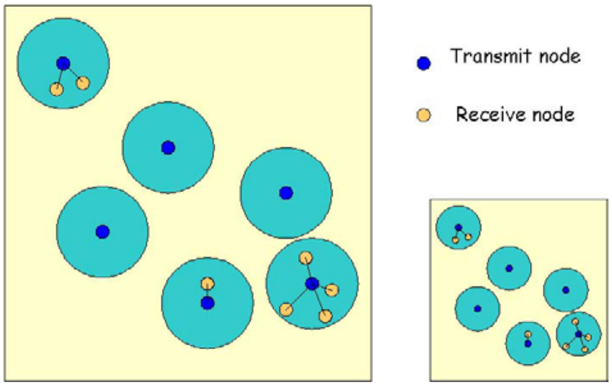

Fig. 3. Illustration of rescaling of two coupled percolation models.

B. Optimum Transmit Range and Scaling Invariance

The existence of an optimal range for capacity maximization is intuitively obvious. When the transmit range is too large, a transmit node may connect to a receive node that is not close. Although there are more simultaneous transmissions over an area, the increase in the mutual interference reduces the achievable rate for each transmit receive node pair considerably. On the other hand, when the transmit range is too small, only node pairs in close proximity transmits. High spectral efficiency of individual links can be obtained due to the reduction of interference power. Few candidate transmit nodes actually transmits, however, since very few receive nodes are very close to the candidate transmit nodes. Thus, the potential spatial transmission concurrency is not fully utilized, leading to a poor capacity per unit area usage.

A couple of interesting observations can be drawn from our numerical results. First, the optimal range r_0 shrinks as node density increases. As node density increases, it is more likely for a transmit node to find receive nodes at a smaller range. A decrease in the transmit range does not adversely affect the number of simultaneous transmissions in the network. Moreover, the optimal range shrinks in a way such that the expected number of neighbors of a candidate transmit node N is constant. Similarly, the optimal fraction of transmit nodes θ is also invariant to node density. Finally, the expected capacity per unit area is linearly increasing with node density. These observations are inter-related and can be explained using the *rescaling* argument drawn from continuum percolation theory [6].

A percolation model is characterized by a point process and a connectivity function. In our context of a homogeneous spatial Poisson process, the point process is completely characterized by the node density λ. A connectivity function, on the other hand, specifies the probability that a link exists between two nodes as a function of distance r between them. Here we are using the on-off random connection model, in which two nodes are connected w.p. 1 when their distance is less than r, which is the same as our artificial transmit range r_0. We denote our percolation model as $\Pi(\lambda, r)$. Any network topology with node density λ and transmit range r is therefore a realization of the percolation model $\Pi(\lambda, r)$.

With reference to Figure 3, realizations of two percolation models $\Pi(\lambda_1(\theta_1), r_1)$ and $\Pi(\lambda_2(\theta_2), r_2)$ are drawn. The two realizations are *coupled* in the sense that the second realization is exactly identical to the first except for the distance scaling in the 2-dimensional space. Accordingly, the following rules must be satisfied.

$$\theta_1 = \theta_2, \tag{17}$$
$$\lambda_1 A_1 = \lambda_2 A_2, \tag{18}$$
$$\lambda_1 r_1^2 = \lambda_2 r_2^2. \tag{19}$$

Equations (17), (18) and (19) express the conservation of the fraction of transmit nodes, number of nodes in the network area, and number of neighbors of an arbitrary node N. These rules must be observed if the two realizations are scaled versions of each other. Note that the two topology realizations have exactly the same connectivity structure. The SIR of an arbitrary link in realization 1, and the associated link capacity, must be identical to that of the corresponding link in realization 2. Since the capacity of a link depends only on the SIR at the receive node, the equivalence of link SIR in two coupled realizations implies that both realizations have the same sum capacity.

Denote $c(A_i), i = 1, 2$ as the sum capacity of realization 1 and 2, where A_i is the network size of realization i. Using the technique of coupling, for each realization of one percolation model $\Pi(\lambda_1, r_1)$, we can always find an equivalent realization in the rescaled percolation model $\Pi(\lambda_2, r_2)$. Taking the expectation over all realizations, we deduce that

$$E[c(A_1)] = E[c(A_2)]. \tag{20}$$

Suppose θ_1 and r_1 jointly maximize $E[c(A_1)]$. From rescaling we know that the optimal θ_2 and r_2 that maximizes $E[c(A_2)]$ must satisfy $\theta_1 = \theta_2$ and $\lambda_1 r_1^2 = \lambda_2 r_2^2$. That is, the number of neighbors of a node N, and the fraction of transmit nodes θ are constant.

The linear increase in expected capacity per unit area is a direct consequence of rescaling in percolation models. The corresponding capacity per unit area for percolation model 1 and 2 are $c(A_1)/A_1$ and $c(A_2)/A_2$. Taking expectations over all coupled realizations, we have

$$E[C_2] = E[C_1]\frac{A_1}{A_2} = E[C_1]\frac{\lambda_2}{\lambda_1}. \tag{21}$$

Let $\lambda_1 = 1$, we obtain

$$E[C_2] = \lambda_2 E[C_1]. \tag{22}$$

That is, the expected capacity per unit area is linearly increasing with node density. The slope corresponds to the expected capacity per unit area for unit node density.

In Figure 4, we compare the capacity of the four strategies. The non rate-adaptive strategy has the worst performance, as expected, with $E[\overline{C}]/E[\underline{C}] = 1.68$. The closest node within range strategy outperforms the random node within range strategy by a small margin ($E[\overline{C}]/E[C_{rand}] = 1.04$). At the optimal range, the average number of nodes within the transmit range is between 0.6 to 1.2 for the four strategies. Thus, most of the time a random node is exactly the same as the closest node. This explains the close performance of the two strategies. The GT strategy, however, has a capacity that is almost halfway between the closest neighbor in range strategy and the non rate-adaptive strategies, with $E[\overline{C}]/E[C_{GT}] = 1.25$. Although the GT strategy is rate-adaptive, an unconstrained transmit range allows connection to a distant receive node in some instances.

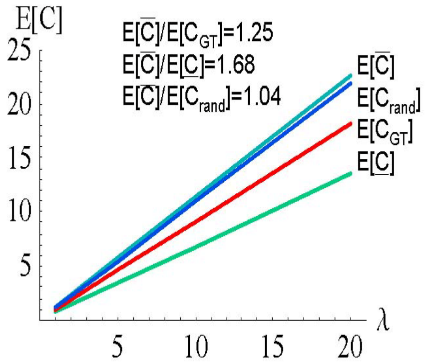

Fig. 4. The expected sum rate per unit area for the four strategies vs. node density λ.

By stipulating a transmit range that excludes transmissions to distant nodes, only good channels are exploited and network interference is reduced.

C. Optimum Point of Network Operation

It is also instructive to compare the optimal values of the fraction of transmit nodes θ, number of neighbors N of a node and the probability of a node transmission for all the strategies. A node is selected as a candidate transmitter with probability θ. For the GT strategy, a candidate node always transmits to the closest neighbor. Thus the probability that an arbitrary node transmits is θ. For the random and closest node in range strategies, the candidate node transmits with probability $(1 - e^{-(1-\theta)N})$ when the transmitter sees some receive nodes are in range. Thus an arbitrary node transmits with probability $p_T = \theta(1 - e^{-(1-\theta)N})$. The values for the four strategies are summarized in Table I. We observe that the optimal value of θ is

Capacity	$E[\underline{C}]$	$E[C_{rand}]$	$E[\overline{C}]$	$E[C_{GT}]$
θ	0.533	0.555	0.531	0.364
N	0.558	0.964	1.17	n/a
p_T	0.1223	0.1936	0.2243	$\theta = 0.364$

TABLE I
OPTIMIZED PARAMETERS FOR THE FOUR STRATEGIES.

close to 0.5 in all strategies except GT. A connection is made up by a transmit and receive node pair. If either kind of nodes are dominant in the network, the scarcity of the other kind of nodes adversely affect the number of transmit and receive node pairs in proximity. A fraction θ close to 0.5 conforms to our intuition and enables a nice mix of transmit and receive nodes over space for creating numerous excellent channels. The observation that θ is slightly larger than 0.5 for all strategies indicates that the transmit nodes has a slightly more influential role in the creation of connections as hinted by the sender-centric approach. In the GT strategy, however, the optimal $\theta = 0.364$ is smaller than 0.5. Since there is no constrained transmit range, a high receive node density is needed to ensure the nearest receive node is actually nearby the transmit node.

The optimal number of neighbors N increases from 0.56 to 1.17 as we move from the non rate-adaptive to the closest node in range strategy. The non rate-adaptive strategy should be operated at a small range, since the link capacity at any point inside the transmit range boundary is not fully utilized. For the adaptive strategies, the random node in range strategy should be operated at a smaller range, to minimize the opportunity cost in case the random node is not the closest receive node. The closest node strategy is not penalized for having a larger transmit range compared to the other two strategies. The shortest link to a receive node is always chosen for connection.

The probability of transmission p_T also increases from 0.1123 to 0.2243 as we move from the non rate-adaptive to the closest node in range strategy. Since θ is similar in the strategies, the probability of transmission is dictated by N. The non rate-adaptive strategy is penalized severely for having a large transmit range. A transmission is attempted when a receive node is close by, at a transmission probability of 0.1223. Thus a sacrifice of spatial transmission concurrency is traded for more spectral efficiency of individual links. On the other hand, the GT strategy has a large transmission probability, more than 50% larger than the closest node in range strategy. Since all candidate transmit nodes transmit in the GT strategy, maximum spatial concurrency is attained at the expense of increased network interference and decreased spectral efficiency in individual links. The comparison of the four strategies in Figure 4 shows that both the non rate-adaptive and the GT strategy have inferior performance versus the adaptive strategies with a stipulated transmit range. This suggests that an optimal tradeoff exists between spectral efficiency and spatial concurrency such that the overall capacity per unit area is maximized.

IV. Discussion

We have examined four transmission strategies in this paper, and showed that rate-adaptive strategies with a stipulated transmit range perform substantially better than the GT strategy with an unconstrained transmit range. Our results imply there is a tradeoff between the spatial transmission concurrency and the spectral efficiency of each transmission. In order to maximize the capacity per unit area, it is necessary to limit the number of simultaneous transmissions to reduce the network interference power such that the SIR and the spectral efficiency of other connections are improved. Moreover, the random node within range strategy has a performance that is close to the closest node in range strategy. Thus a designer of multiple access protocols only needs to focus on contention of local channel when several receive nodes are in proximity. There is little need of a scheduling algorithm for prioritized transmissions based on distance or received power.

The results shown in Table I show that the optimum range of our strategies is between 0.6 to 1.2 neighbors, independent of node density. These results can be contrasted to the results in [3, 5, 13], which suggested that a magic number of 6 to 8 neighbors, or a scaled version of that number to account for the processing gain in spread spectrum systems [11] and second order effects of the channel [18], is optimum. In these works, a hypothetical line is drawn from a source to the destination node. The transmit range is chosen such that the the expected distance advance in one transmission projected to this line is maximized. This performance metric is called the *forward progress* in the literature. The concept of forward progress is predicated on the assumption that mobile nodes communicate using multihop routing. What we have shown in this paper suggests that capacity

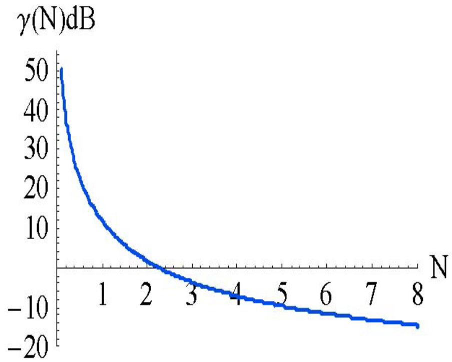

Fig. 5. Illustration of SIR γ as a function of number of neighbors N.

per unit area of one network snapshot can be fully utilized only if each transmit node sees about one neighbor node on the average. Our results demonstrate that the mobile infostation network is a paradigm that fits into this optimization criterion.

To appreciate the potential improvement in *link capacity* over the multihop paradigm, we plot the expected SIR $\gamma(N)$ at the transmit range boundary as a function of number of neighbors of a node in Figure 5. As the number of neighbors N increase from 1 to 8, the SIR at the range boundary drops from 15dB to -15dB, a factor of 1000. The corresponding link capacity of a mobile infostation connection is over 100 times that of a multihop forwarding connection. The dramatic improvement in link capacity, together with [1] which explicitly shows that the sum capacity in each network snapshot is sustainable in the long run, demonstrates that a much larger end-to-end throughput capacity is realizable for mobile infostation networks.

Recall that [1] showed the mobile infostation paradigm allows a network throughput that is scalable to the number of nodes. We have obtained exact capacity per unit area expressions as a function of transmit range, the fraction of candidate transmit nodes and node density. It turns out that the mobile infostation paradigm not only improves the spectral efficiency of a link over the multihop paradigm. It is somewhat surprising to find out that the spectral efficiency per unit area is linearly increasing with node density in mobile infostation networks. This is counter-intuitive since an increase in the node density is often accompanied by a corresponding increase of network interference. However, a mobile infostation also shrinks the transmit range such that the number of nodes within the transmit range remains constant. Thus, a mobile infostation also exploits the increase in physical proximity of the receive nodes as node density increases. The contrasting effects of increasing signal strength and increasing interference power at high node density work together that brings about the independence of link SIR's to node density. At high node density, the same sum capacity can be achieved at a smaller area, leading to an increase in capacity per unit area. This result has far reaching implications for the feasibility of future pervasive computing environments. The proliferation of mobile devices makes the deployment of dense node networks in the future almost a certainty. Unfortunately multihop networks suffers from the curse of node density. The excessive need of multihop forwarding in high node density environments drives the achievable per-node throughput to zero. In contrast, node density is a blessing in mobile infostation networks. The increase in interference power due to increased node density is counter-balanced by the improved channel due to the proximity of receive nodes at high node density. Since nodes are packed closer in high node density scenarios, better spatial concurrency is achieved, leading to an increase in capacity per unit area. Our results show that the capacity per unit area for mobile infostations actually increases linearly with node density.

In retrospect, we have looked into the optimal transmit range and the theoretical and practical achievable rate per unit area of mobile infostation networks. The concept of transmit range is novel in the paradigm of mobile infostations. Capacity equations are derived for four strategies and we show that a stipulated transmit range improves capacity. Though it is not obvious in the problem formulation, the optimal number of neighbors of a node, and the fraction of nodes as candidate transmit nodes is invariant to node density. Comparisons have been made to the well known magic number of 6 to 8 neighbors, reflecting the contrasting optimization criteria for the multihop networking and mobile infostations paradigm. Another finding is that the capacity per unit area is linearly increasing with node density. This can be explained by a rescaling argument drawn from percolation theory. This has implications in the design of ad hoc networks in future pervasive networking environments with high node density.

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