An Upper Bound of Node Density in Cooperative Networks with Selfish Behavior

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***Abstract*—In a wireless network, connectivity is arguably the most critical issue that requires significant study since a network can hardly function well if it is disconnected. On the other hand, there are extraordinary interests in exploiting cooperative techniques in wireless networks in recent years. This paper studies the connectivity problem of large cooperative ad hoc networks. Unlike traditional cooperative networks where all nodes are willing to transmit in a collaborative manner, the cooperative network we considered does not assume that all nodes would like to transmit cooperatively when relaying other nodes' traffic. In other words, each node exhibits some sense of selfishness. Specifically, we model nodes in such a way that each node cooperatively transmits with p-selfishness or location-based p-selfishness when relaying other nodes' traffic. For the considered network, we assume that nodes are generated according to a Poisson Point Process (PPP) and techniques based on stochastic geometry and percolation theory are used to analyze the connectivity in such system. To quantify the performance of the cooperative ad hoc network with selfish behavior, we provides an upper bound of node density for such network to maintain connectivity.**

I. Introduction

In a wireless network, a node can directly communicate with other nodes within its range. A pair of wireless nodes is said to be 1-hop connected if they are within the range of each other. For a wireless multi-hop network, a pair of wireless nodes is said to be n-hop connected if there are $n-1$ hops in between them. Obviously, n-hop connectivity depends on 1-hop connectivity and it increases with node density and/or communication range.

Due to shadowing, fading and mobility, while connectivity [1] is arguably the most critical performance metric for a wireless network to function well, one can not always ensure that any two nodes keep connected at all times, especially when these two nodes are several hops away. When Node A loses its connectivity to Node B, A will not be able to communicate with B and the transmission fails. Because ad hoc nodes are typically randomly located in the network, full connectivity of the whole network is generally not possible, otherwise it would require extremely large node density (or range) that is economically prohibited, for all nodes to stay connected. In practical implementation of a large ad hoc network, it is often sufficient for the network operator to ensure that a large fraction of nodes instead of all nodes in the network are connected.

It is known that in a network of infinite size, a giant (*i.e.,* infinitely large) component will appear once the node density or range is above some threshold. This giant component has infinite nodes and all nodes in the giant component are fully connected. The occurrence of such giant component is referred to as percolation. For a wireless network to function well, the network operator should ensure that percolation occurs. According to percolation theory, a network is called in the sub-critical phase, critical phase or super-critical phase when the node density (or range) is less than, equal to or greater than the critical density (or critical range), respectively. As it is not practical to change node range on the fly, a feasible policy is to increase node density instead of node range to make the network percolative.

Stochastic geometry [2] and percolation theory [3] are the two most helpful tools for analyzing the connectivity property of a wireless network. Stochastic geometry allows to study the average behavior over many spatial realizations of a network whose nodes are placed according to some probability distribution. It has been used to characterize interference in wireless networks [4]. It is also used to model the random channel effects such as path loss, fading, shadowing, and combinations thereof. In recent years, stochastic geometry has been applied to various wireless systems [5] such as cellular networks [6], [7], cooperative or relay networks [1], [8] and cognitive radios [9].

Among various approaches for connectivity in wireless networks, cooperative communication shows great potential for substantially improving connectivity. The rationale for the extraordinary interest in exploiting cooperative techniques in wireless networks is very clear, as demonstrated by the high volume of publications in recent years [10], [11], [12], [13], [14], showing concrete advantages and potentials of cooperation. The collaborative interaction of different entities does pay off in virtually any network, regardless of access technologies, protocols, architectures and network scenarios. The benefits of cooperation in wireless network are manifold,

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to name a few, improving connectivity, increasing throughput, extending coverage and achieving higher efficiency in resource utilization.

From a wider perspective, the challenges of achieving cooperation are not just technical but indeed multi-disciplinary, involving for instance understanding individual and social behavioral patterns and their impact on the technology, architecture, operation and ultimately performance of a wireless network. An important point about cooperative networks in practical scenarios is the fact that, in addition to the purely technical cooperation, user's decision on joining such a network and its manner to cooperate are integral parts of the whole cooperative process [15]. As users are an important part of the cooperative game, new aspects related to the social interaction among users will come into the scene, like incentives to foster user cooperation, users' selfish nature, users' e-reputation, security and privacy issues and others. Putting these together, it is of great interest to investigate the connectivity problem in cooperative networks with added social interaction between users. Unfortunately, for cooperative networks, the connectivity problem and the social interaction between users are separately considered [16], [1], [15].

Our ultimate objective is to quantify the connectivity for large scale cooperative ad hoc networks with the social interaction between users. A key point here is to find the social behavioral pattern for nodes in cooperation and also be able to define such pattern mathematically. As a first-step on this direction, this paper asymptotically studies the connectivity problem of cooperative networks with selfish behavior that can be characterized by some relatively simple metrics.

The rest of the paper is structured as follows. In Section II, we first introduce basic terminology and techniques in analyzing the connectivity properties in wireless networks. We then describe the connectivity problem for large scale k-collaborative cooperative networks with selfish behavior. After that, Section III analyzes the connectivity and provides upper bounds on the critical node density for such networks with two selfish patterns, respectively. Finally, in Section IV, we present numerical results to illustrate the impact of cooperation with selfishness on the critical node density, followed by the conclusion in Section V.

II. System Model

Before we turn our attention to the connectivity in cooperative networks, we first describe the connectivity problem in wireless networks and recapitulate basic terminology and techniques used in analyzing it.

A. Connectivity in Wireless Networks

A pair of wireless nodes is said to be 1-hop connected if they are within range, a distance determined by the required signal-to-noise ratio (SNR), the transmission power, and the path loss. In a wireless multi-hop network, a pair of wireless nodes is said to be n-hop connected if there are n connected hops in between them. While connectivity is arguably the most critical performance metric for a wireless network, it is not true to assume that any two ad hoc nodes keep connected at all times, especially when these two nodes are several hops away. Because ad hoc nodes are typically randomly located, full connectivity of the whole network is generally not available. Hence, in practical large ad hoc network, it is more appropriate to ensure that some fraction of nodes instead of all nodes in the network are connected. In other words, the network operator needs to ensure some degree of connectivity but not necessarily full connectivity.

In studies of the connectivity in wireless networks, stochastic geometry [2] and percolation theory [3] are the two most helpful tools. In the following, we introduce basic terminology in these two tools and recapitulate two existing lemmas.

B. Stochastic Geometry and Percolation Theory

Stochastic geometry [2] greatly facilitates the research on the average behavior over many spatial realizations of a network whose nodes are placed according to some probability distribution.

In the theory of stochastic geometry, a Poisson point process (PPP) [5] is commonly used to quantify the node distribution. [5] provides the following property for PPP.

Lemma 1 (PPP Distance) *If nodes are distributed according to a PPP with node density λ, the probability that the distance d between a node and its nearest neighbor is less than R is*

$$Prob\{d \leq R\} = 1 - e^{-\pi R^2 \lambda} \tag{1}$$

Mathematically, by Kolmogorov's zero-one law, in a network of infinite size, a giant component will appear once λ or r is above some threshold. All nodes in the giant component are fully connected. The density (or range) threshold for a giant component to occur is called the critical density (or range), denoted by λ_c (or r_c) . By percolation theory, a giant component will never exist if the node density λ (or range r) is less than the critical density λ_c (or critical range r_c), and a giant component will almost surely occur once $\lambda > \lambda_c$ (or $r > r_c$). This interesting phenomenon is referred to as percolation. For a wireless network to function well, the network operator should ensure that percolation occurs. According to percolation theory, a network is called in the sub-critical phase, critical phase or super-critical phase when $\lambda <,=,> \lambda_c$ ($r <,=,> r_c$), respectively. Theoretically, one can increase the node density and/or range for percolation to occur. In real systems, it is not practical to change node range on the fly due to the ad hoc characteristic of nodes. A feasible policy then is to increase node density instead of range until the network percolates.

Percolation theory [3] also proved that, given a node n_0 in the network, if n_0 belongs to a giant component with positive probability, the network is then percolative. From percolation theory, we have the following important lemma on connectivity [5]

Lemma 2 (Scale Property) *A 2-dimensional network with a range r and a node density λ has the same connectivity* *properties as a 2-dimensional network with a range $a \cdot r$ ($a > 0$) and a node density $\frac{\lambda}{a^2}$*

C. Connectivity in Cooperative Network with Selfish Behavior

Now consider a cooperative ad hoc network shown in Fig. 1. We assume that k nodes $n_0 \sim n_{k-1}$ transmit to Node n_k in a cooperative manner. These k nodes form a k-collaborative cluster. Because of cooperative transmission, the distance between n_k and $n_i (i = 0 \sim k-1)$ could be greater than node range r. Node n_k and $k-1$ nodes out of $n_0 \sim n_{k-1}$ together form another k-collaborative cluster and will reach Node n_{k+1}. Obviously, this new cluster is connected with the previous one.

In most work on cooperative transmission, it is assumed that all nodes in a cluster are willing to cooperatively transmit at all time. This assumption is not true especially when nodes have some intelligence or social characteristic such as self-awareness. For example, nodes may become selfish in relaying other nodes' traffic and would not cooperatively transmit at some time. In one configuration, nodes are only willing to cooperative transmit other nodes' traffic with some fixed probability p. The extreme case of $p = 0$ corresponds to the non-cooperative scenario. In another configuration, nodes become more intelligent and are willing to cooperatively transmit other nodes' traffic with a probability related to their own residual energy, relative location to the destination, *etc.* In such cases, we say that these k nodes form a k-collaborative cluster with selfishness. Obviously, different selfish patterns correspond to different connectivities in the considered system.

To perform asymptotic analyses for the connectivity, we assume a cooperative network of infinite size. No matter how selfish a node would be, if we increase the number of nodes in each cluster to make the cooperation strong enough so that each cluster could almost surely reach another nodes outside it, a cluster chain of infinite size will almost surely appear and percolation occurs in the considered network. Our job now is to analyze the k-collaborative connectivity problem for a cooperative network with selfish behavior . To be specific, we want to answer the question how many nodes are needed in each cluster for percolation to occur in a cooperative network with selfishness?

III. Analysis of k-Collaborative Connectivity with Selfishness

For achievability for cooperative ad hoc networks, we do not use complex code designs such as distributed transmit beamforming [17] that requires precisely phasing transmissions. Instead, we use the distributed frequency-shift keyed (FSK) cooperation method proposed in [1]. The distributed FSK cooperation scheme does not require phase coherence at the transmitters and represents a worst case of cooperation that achieves only power summing.

Refer to Fig. 1, we consider a 2-dimensional cooperative network of infinite size. Nodes are distributed across an infinite region according to a PPP with node density $\lambda > 0$. k-collaborative connectivity for such network is defined as the existence of one cluster chain containing an infinite number of connected clusters, each of which has k nodes cooperatively transmitting in a selfish manner.

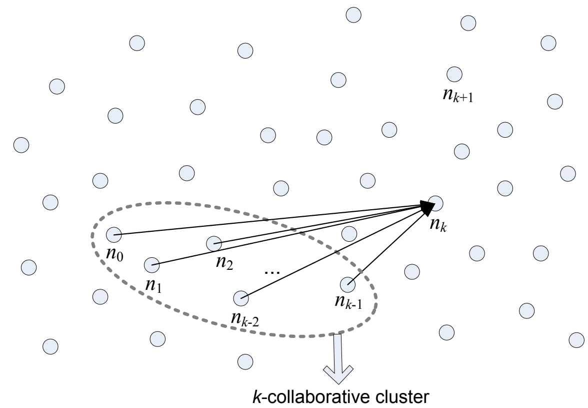

Fig. 1. k-Collaborative Connectivity

We assume that each node transmits with power P_t and denote the received power at reference distance r_0 as P_0. We assume a path loss attenuation function in the form of a power law, *i.e.,* without node cooperation, the received power at distance d is

$$P_d = P_0 \times \left(\frac{d}{d_0}\right)^{-\alpha} \tag{2}$$

where α is the path loss exponent.

Let r be the node range. P_r will be the receiving power required for successful receive at a node. In other words, for any Node k to successfully receive, the receiving power P_k should be greater than P_r,

$$P_k \geq P_r = P_0 \times \left(\frac{r}{d_0}\right)^{-\alpha} \tag{3}$$

We use $d_{i,j}$ to denote the distance between two nodes n_i and n_j, and $P_{i,j}$ the power at Node n_j received from Node n_i. Refer to Fig. 1, with node cooperation, the received power at Node n_k depends on the power received from each branches and also on the selfish pattern of nodes. In the following, we consider two simple models to describe the selfish behavior of nodes.

A. p-Selfish Cooperation

With this model, a node in a k-collaborative cluster will cooperatively transmit with a fixed probability p when relaying other nodes' traffic. Refer to Fig. 1, without loss of generality, we assume that Node n_{k-1} has data for Node n_k and it transmits to n_k with probability 1 while the remaining $k-1$ nodes in the cluster cooperative with n_{k-1} and transmit to n_k with probability p. The extreme case of $p = 0$ corresponds to non-cooperative transmission while the extreme case of $p = 1$ corresponds to traditional cooperative transmission without considering the selfish behavior of nodes. Since we are using the distributed FSK scheme [1] for node cooperation,

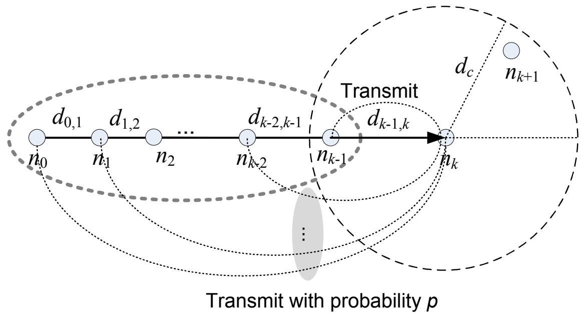

Fig. 2. Worst-Case Cooperation: p-Selfishness

the received power P_k at Node n_k is simply the power sum of all branches. With p-selfish cooperation, we have

$$\begin{aligned} P_k &= \sum_{i=0}^{k-1} P_{i,k} = P_{k-1,k} + \sum_{i=0}^{k-2} P_{i,k} \\ &= P_0 \times \left(\frac{d_{k-1,k}}{d_0}\right)^{-\alpha} + \sum_{i=0}^{k-2} p \times P_0 \times \left(\frac{d_{i,k}}{d_0}\right)^{-\alpha}. \quad (4) \end{aligned}$$

Now consider the worst case of cooperative transmission in a cluster. The worst case cooperation is the one that produces the minimum power at n_k. Refer to Fig. 2, the worst case corresponds to the topology where n_k and all nodes in the cluster are on a line.

Theorem 3 (Worst-Case Cooperation) *The worst-case k-collaborative transmission corresponds to a linear topology where Node n_k and all k cooperative nodes in a cluster are on a line.*

Proof: $\forall i = 0 \sim k-2$, with triangle inequality, we have $d_{i,k} \le \sum_{i=0}^{k-2} d_{i,i+1} + d_{k-1,k}$. Denote P_k^L the power at Node n_k received from the linear topology cluster shown in Fig. 2. With (4), for a cluster of any topology, the received power P_k satisfies

$$\begin{aligned} P_k &= P_0 \times \left(\frac{d_{k-1,k}}{d_0}\right)^{-\alpha} + \sum_{i=0}^{k-2} p \times P_0 \times \left(\frac{d_{i,k}}{d_0}\right)^{-\alpha} \\ &\ge P_0 \times \left(\frac{d_{k-1,k}}{d_0}\right)^{-\alpha} \\ &+ \sum_{i=0}^{k-2} p \times P_0 \times \left(\frac{\sum_{m=i}^{k-1} d_{m,m+1}}{d_0}\right)^{-\alpha} = P_k^L. \quad (5) \end{aligned}$$

This completes the proof. ∎

Define a positive d_c so that $d_c \ge \max_{i=0,\cdots,k-1} d_{i,i+1}$. We have,

$$\begin{aligned} P_k^L &= P_0 \times \left(\frac{d_{k-1,k}}{d_0}\right)^{-\alpha} \\ &+ \sum_{i=0}^{k-2} p \times P_0 \times \left(\frac{\sum_{m=i}^{k-1} d_{m,m+1}}{d_0}\right)^{-\alpha} \\ &\ge P_0 \times \left(\frac{d_c}{d_0}\right)^{-\alpha} \\ &+ \sum_{i=0}^{k-2} p \times P_0 \times \left(\frac{\sum_{m=i}^{k-1} d_c}{d_0}\right)^{-\alpha} \\ &= P_0 \times \left(\frac{d_c}{d_0}\right)^{-\alpha} \times \left(1 + \sum_{i=0}^{k-2} p \times (i+2)^{-\alpha}\right). \quad (6) \end{aligned}$$

Obviously, if the right-hand-side (R.H.S) of (6) satisfies

$$P_0 \times \left(\frac{d_c}{d_0}\right)^{-\alpha} \times \left(1 + \sum_{i=0}^{k-2} p \times (i+2)^{-\alpha}\right) = P_r. \quad (7)$$

, we will have $P_k \ge P_k^L \ge P_r$, *i.e.,* the k-collaborative cluster with p-selfishness in Fig. 1 can cooperatively transmit to Node n_k successfully.

With (7) and the R.H.S of (3), we have

$$d_c = r \times \left(1 + \sum_{i=0}^{k-2} p \times (i+2)^{-\alpha}\right)^{\frac{1}{\alpha}}. \quad (8)$$

Obviously, d_c represents the effective range of the linear topology cluster. (8) and $d_c \ge \max_{i=0,\cdots,k-1} d_{i,i+1}$ together ensure that the k-collaborative cluster of any topology $(n_0, n_1, \cdots, n_{k-1})$ successfully transmits to n_k under the p-selfishness assumption.

With the above discussion, we have the following theorem

Theorem 4 (p-Selfishness) *For a k-collaborative network with p-selfishness, the critical node density λ_c^* is upper bounded by*

$$\lambda_c^* \le \frac{\lambda_c}{\left(1 + \sum_{i=0}^{k-2} p \times (i+2)^{-\alpha}\right)^{\frac{2}{\alpha}}}. \quad (9)$$

where λ_c is the critical node density for the non-cooperative network.

Proof: Refer to Fig. 1, for a given node n_0 in the cooperative network of infinite size, we find its nearest neighbor n_1 on the right side of n_0. Similarly, we find n_2 for n_1, $\cdots$, until we find n_k for n_{k-1}. Nodes $n_0 \sim n_{k-1}$ form a k-collaborative cluster to n_k. Given a positive d_c defined by (8), $\forall i = 0, \cdots, i-1$, we denote by E_i the event that $d_{i,i+1} \le d_c$ and n_{i+1} is on the right side of n_i. We then have $Prob\{E_i\} = \frac{1}{2} Prob\{d_{i,i+1} \le d_c\}$. Since $Prob\{E_0 \bigcap E_1 \cdots \bigcap E_{i-1}\} = \left(\frac{1}{2}\right)^{k-1} (Prob\{d_{i,i+1} \le d_c\})^{k-1}$, applying Lemma 1, we have

$$Prob\{E_0 \bigcap E_1 \cdots \bigcap E_{i-1}\} = \left(\frac{1}{2}\right)^k \left(1 - e^{-\pi {d_c}^2 \lambda}\right)^k. \quad (10)$$

As mentioned earlier, (8) and $d_c \ge \max_{i=0,\cdots,k-1} d_{i,i+1}$ together ensure that the k-collaborative cluster (of any topology) with p-selfishness $(n_0, n_1, \cdots, n_{k-1})$ transmits to n_k. If n_{k+1} is within a distance d_c away from n_k, we will have $d_c \ge \max_{i=1,\cdots,k} d_{i,i+1}$. Obviously, $n_1, n_2, \cdots, n_{k-1}$ and

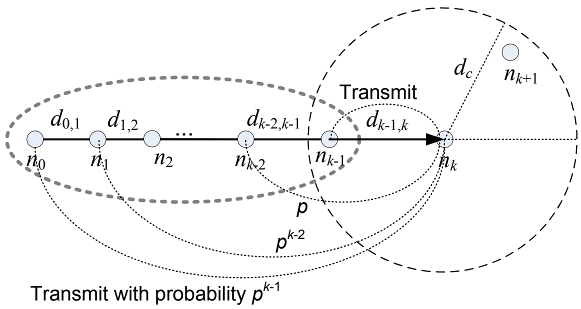

Fig. 3. Worst-Case Cooperation: Location-Based p-Selfishness

n_k will further form a new k-collaborative cluster that can transmit to n_{k+1}. This procedure continues and an infinite cluster chain containing the given node n_0 appears almost surely. With (10), we know that the infinite cluster chain appears with non-zero probability, which make the network percolative.

Let r^* be the effective range of the cluster. Since d_c is obtained for the worst-case cooperation and represent the effective range of the linear topology cluster, we have $d_c \leq r^*$. Let λ_c^* be the critical node density for the k-collaborative network to percolate. According to the scale property (Lemma 2),

$$\lambda_c^* = \lambda_c \times (r/r^*)^2 \leq \lambda_c \times (r/d_c)^2. \tag{11}$$

where λ_c is the critical node density for the non-cooperative network to percolate.

Substituting (8) into (11) completes the proof. ■

B. Location-Based p-Selfish Cooperation

With this model, a node in a k-collaborative cluster will cooperatively transmit with a location-related probability when relaying other nodes' traffic. Refer to Fig. 1, without loss of generality, we assume that Node n_{k-1} has data for Node n_k and it transmit to n_k with probability 1 while the remaining $k-1$ nodes in the cluster cooperative with n_{k-1} and transmit to n_k with location-related probability. Like what we have done for p-selfishness, for this model we consider the worst case scenario shown in Fig. 3.

As shown in Fig. 3, we use a simple scheme for location-based p-selfishness, *i.e.,* Node n_i ($i = 0 \sim k-2$) cooperatively transmit to n_k with probability p^{k-i-1}. Similar to the p-selfishness model, for the location-based p-selfishness model, the extreme case of $p = 0$ corresponds to non-cooperative transmission while the extreme case of $p = 1$ corresponds to traditional cooperative transmission without considering the selfish behavior of nodes. Using the same technique as in the p-selfishness model, we state without proof the following theorem.

Theorem 5 (Location-Based p-Selfishness) *For a k-collaborative network with location-based p-selfishness, the critical node density λ_c^* is upper bounded by*

$$\lambda_c^* \leq \frac{\lambda_c}{\left(1 + \sum_{i=0}^{k-2} p^{k-i-1} \times (i+2)^{-\alpha}\right)^{\frac{2}{\alpha}}}. \tag{12}$$

where λ_c is the critical node density for the non-cooperative network.

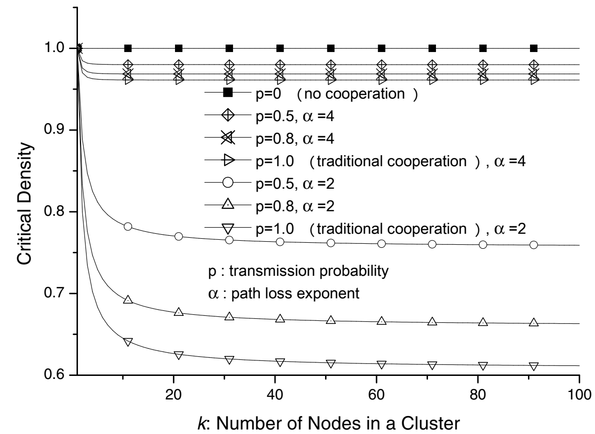

Fig. 4. Critical Density in Cooperative Networks with p-Selfishness

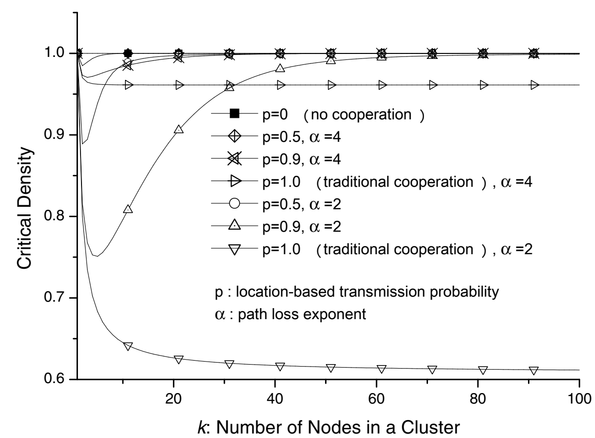

Fig. 5. Critical Density in Cooperative Networks with Location-based p-Selfishness

IV. Numerical Experiments

We use (9) and (12) to numerically evaluate the critical density for a k-collaborative network to percolate. In the experiments, the critical density for the non-cooperative network is normalized to be 1. We plot in Fig. 4 and Fig. 5 the upper bounds of the critical density for two selfish models under various k and path loss exponent α.

We can see from Fig. 4 that, for p-selfishness, when nodes would like to cooperate with probability of $p = 0.8$, the number of nodes needed in a cooperative network is about 70% of what is needed in a non-cooperative network, for the configuration: $k = 10, \alpha = 2.0$.

We can see from Fig. 4 that, for location-based p-selfishness, when nodes would like to cooperate with probability of $p = 0.9$, the number of nodes needed in a cooperative network is about 80% of what is needed in a non-cooperative network, for the configuration: $k = 10, \alpha = 2.0$. Note that for $k = 10$, $p = 0.9$ in the location-based p-selfish model corresponds to a probability of 0.61 in the p-selfish model for the same average probability of transmission (*i.e.,* both have the same number of cooperative transmission).

V. Conclusion

We analyze the connectivity for k-collaborative network with selfishness. Unlike traditional cooperative networks where all nodes are willing to transmit in a collaborative manner, in our research, the cooperative network does not assume that all nodes would like to transmit cooperatively when relaying other nodes' traffic. Specifically, we model nodes in such a way that each node cooperatively transmits with p-selfishness or location-based p-selfishness when relaying other nodes' traffic. For the considered network, we use stochastic geometry and percolation theory to study the connectivity problem. Finally, we provide upper bounds of node density for two selfish models.

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