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UNIVERSITY OF CALIFORNIA, SAN DIEGO

An Analytical and Simulation Study of Wireless Ad Hoc Networks With and Without Cooperation

A dissertation submitted in partial satisfaction of the
requirements for the degree
Doctor of Philosophy

in

Department of Electrical Engineering

by

Louisa Pui Sum Ip

Committee in charge:

Professor Anthony S. Acampora, Chair
Professor Massimo Franceschetti
Professor Rajesh Gupta
Professor William Hodgkiss
Professor Joe Pasquale

2010

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The dissertation of Louisa Pui Sum Ip is approved, and it is acceptable in quality and form for publication on microfilm and electronically:

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Chair

University of California, San Diego

2010

EPIGRAPH

Do not go where the path may lead;
go instead where there is no path and leave a trail.
—-Ralph Waldo Emerson

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ACKNOWLEDGEMENTS

There is not enough room nor words to show my gratitude to all those who left a positive footprint in my life. This dissertation is not worthy enough to dedicate to them and I endeavor to continue my studies so that my future contributions will be.

My hope is that however humble my contribution is to the wireless ad hoc network community, someone can benefit from my research and presentations. While it may be a researcher's dream to achieve great discovery, research leading to a path best avoided is equally worth reading. My dad once said sometimes it is more rewarding to lose a game of chess, than win one. It is through failure that we learn from our mistakes. By learning from our mistakes we better ourselves for the next challenge that comes our way. His wisdom has been my guiding light for each dead end I ran into. Smooth sailing would have taken all the fun out of this incredible journey.

My journey could not be complete without a leader, a visionary, and a believer. I found all these qualities in my advisor, Anthony Acampora. He was always ten steps ahead, anticipating early on what might be the results but still allowed me to experiment and grow. We faced many wrong turns together, and met up at ungodly hours and weekends correcting and perfecting our algorithms. By the time I realized my way was not a path forward, Professor Acampora already had visualized the next step. He knew just the right questions to ask to keep me thinking and analyzing where I went wrong. In the computer scientists' world, he would have been the walking debugger! Because he believed in me, I am forever grateful.

I am also grateful to my committee members: Dr. Bill Hodgkiss, Dr. Massimo Franceschetti, Dr. Rajesh Gupta, and Dr. Joe Pasquale, for giving me a constructive review and an opportunity to be at where I am today. Their comments and suggestions expanded my horizon; from my tiny bubble of research to an open sea of literature. It was because of them that I pushed to be even more aware of the world outside my comfort zone. I had the tendency to be too content in my little world and unrelentlessly solving my own problems.

Behind every wise man there exists a wiser woman. To Margaret Acampora and my mom.

To Margaret, for graciously sacrificing some of her time with Professor Acampora so that he could spend it with his graduate students.

To my mom, for giving me life (and her endless phone calls reminding me to take my vitamins). She gives my siblings and I a sense of purpose. Somehow, she knew by not clipping our wings, we would fly on our due course.

To the ECE department staff for their extraordinary help through the years, especially when I moved away for a job opportunity in the middle of my study. Many thanks to John Minan, Karol Previte, Megan Scott, and Virginia McIlwain. Staff members are the backbone of any company or university. To use my mom's favorite phrase, I shall repeat her wisdom here to describe how important they are: Without them we would run around in chaos like chickens with their heads cut off.

This dissertation would have been filled with grammatical errors if not for my friend, running buddy, and colleague Hafeez Jaffer. Hafeez, as a thank you for proof reading my dissertation, I won't complain the next time you turn a short 5-mile run into a 20-mile excursion.

Last but never the least, Bryan Chavez and his four-legged-bladder friend Rudder, for reviewing most of my papers even though he had no clues in the subject matter (Bryan, not the dog). For doing most of the cleaning cleaning and cooking the delicious meals to keep me going. For making that important cup of latte each morning so that I had the necessary dose of caffeine for a full day of work and school. To Rudder, for being my companion during the long nights of coding and writing. For jumping on to my keyboard to add that extra few letters of love, needed or not. For sitting on my laptop to remind me that it is equally important to pay attention to life outside of school and work. For loving me and cheering me up whenever I see his scruffy fur. For snoring at night and keeping me awake so that I could finish this dissertation.

Chapter 3, in part, has been submitted for publication as appeared in the following paper: Anthony S. Acampora and Louisa P.S. Ip, "Information Theoretic Bounds

on the Capacity of Peer-to-Peer Wireless Networks with Hop-by-Hop Routing," IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC 2007) and Anthony S. Acampora, Michael Tan, and Louisa P.S. Ip, "Fundamental Bound on the Capacity of Ad Hoc Networks with Conventional Hop-by-Hop Routing," Wireless Communications 2007 CNIT Thyrrenian Symposium, pages 127-133,2007. The dissertation author was the primary investigator and co-author of this paper.

Chapter 4, in part, has been submitted for publication of the material as appeared in the following papers: Anthony S. Acampora and Louisa P.S. Ip. "A Lower Bound on the Capacity of Wireless Ad Hoc Networks with Cooperating Nodes," Ad-Hoc NOW 2008, LNCS 5198, pages 230-240, September 2008, and Anthongy S. Acampora and Louisa P.S. Ip, "Comparison of the Lower Bound for the Capacity of the Wireless Ad Hoc Networks with Cooperating Nodes to the Upper Bound of Conventional Peer-to-Peer Wireless Networks with Hop-by-Hop Routing," Ad Hoc and Sensor Wireless networks: An International Journal," 9(1-2):73-84, 2010. The dissertation author was the primary investigator and co-author of these papers.

Chapter 5, in part is currently being prepared for submission for publication of the material. The dissertation author was the primary investigator and author of this paper.

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Louisa Pui Sum Ip, "Fundus Based Eye Tracker for Optical Coherence Tomography", *Master Thesis*.

Anthony S. Acampora and Louisa P.S. Ip, "Information Theoretic Bounds on the Capacity of Peer-to-Peer Wireless Networks with Hop-by-Hop Routing," *IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC 2007),* pp. 1-5, 2007.

Anthony S. Acampora, Michael Tan and Louisa Ip, "Fundamental Bound on the Capacity of Ad Hoc Networks with Conventional Hop-by-Hop Routing," *Wireless Communications 2007 CNIT Thyrrenian Symposium*, 2007.

Anthony S. Acampora and Louisa Pui Sum Ip, "A Lower Bound on the Capacity of Wireless Ad Hoc Networks with Cooperating Nodes," *Ad-Hoc NOW 2008, LNCS 5198,* pp. 230-240, 2008.

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ABSTRACT OF THE DISSERTATION

An Analytical and Simulation Study of Wireless Ad Hoc Networks With and Without Cooperation

by

Louisa Pui Sum Ip

Doctor of Philosophy in Department of Electrical Engineering

University of California, San Diego, 2010

Professor Anthony S. Acampora, Chair

Wireless ad hoc networks have gained popularity in recent years. A networks' ability to self-organize without a centralized base station and the ease of deployment in a rough terrain make ad hoc networks desirable. Furthermore, for small mobile devices, it is not practical to mount multiple antennas to exploit the benefits of spatial diversity for combating multipath fading. With ad hoc networks, it is possible to take advantage of spatial diversity as nodes may cooperatively act together as if they were multiple antennas. For this dissertation, the system model is first presented to obtain the information-theoretic upper bound for peer-to-peer ad hoc network with hop-by-hop routing. This bound is not physically achievable, but is useful as a yardstick against any node cooperation scheme studied. Using the same system model, lower bound with node cooperation is studied in depth for two cases: simple time-share bound and frequency reuse bound. It is found that having more than two nodes cooperatively transmit together as a relay node does not provide significant improvement over two nodes cooperatively transmitting. The results also indicate that a more elegant scheme must be used

for the frequency reuse case before the lower bound with node cooperation could match the information-theoretic upper bound. The simple scheme used here does not employ interference avoidance strategies beyond selecting nodes which are simultaneously sending must meet certain interference criteria. The results of using this scheme indicate that at a high signal to noise ratio, the bound with cooperation approaches peer-to-peer bound with no cooperation.

Chapter 1

Introduction

1.1 Introduction

Perhaps my earliest contact with a peer-to-peer and hop-by-hop network was the telephone game back in kindergarden. The game starts when the first player in the queue whispers a message to the person behind him. The message is whispered from player to player until the message reaches the last person in the queue. The last player then repeats the message received to the entire group. There is no winner or loser in to the game. Ideally, the message arrives unchanged, however, most likely errors would occur somewhere. The point of the game is perhaps to show that messages can get lost or miscommunicated between players. What is considered success of the game is subjective.

At the time, little did I know years later the telephone game would become the heart of our daily lives. As the digital decade concluded, where instant messages and immediate gratification is no longer just a desire but a minimum requirement, researchers dig deeper into pushing the bounds in communication speed, mobility and accuracy. In the past, the United States Postal Services frequently raised their postage because of the rising of the cost of transportation and minimum wages. The increase in rates is also due to the weaning use of snail mail. Many wonder why they would pay for a postage stamp when they can simply hit the send button.

My research partially addresses the limitation on message delivery. To fully address this issue, it would take intense collaboration from researchers around the world. How fast can one transmit a message and can it be possible to do better than peer-to-peer? The last player might not be within hearing range, but what if one gossips to a group of friends, will the message that gets to the intended listener be faster and more accurate? The same idea goes for the wireless network with node cooperation. The nature of broadcasting enables nearby nodes beside the intended recipient to eavesdrop, why not allow more nodes to cooperatively transmit the message to the intended recipient?

1.2 Related Work and State of the Art

The study of network capacity can be traced back Claude E. Shannon's "A Mathematical Theory of Communication" paper in 1948 [46]. Shannon's source coding theorem predicted the number of bits needed to represent information to be transmitted in an unpredictable event. He called it "entropy" and stated that it is possible to achieve an error free rate given the transmission power, noise power and bandwidth. Entropy, measured in bits, is the amount of information. Entropy increases as the freedom of choice, or uncertainty, increases [36]. This will be apparent in the case where the simulation with Poisson Traffic of mean ten has a higher entropy than the case with Poisson Traffic of mean one. This is because the uncertainty increased in the mean ten case. The entropy, ϵ, is the negative of the sum of the probability times the logarithm of the probability. For the case with two probabilities:

$$\epsilon = -(p_o \log_2 p_o + p_1 \log_2 p_1). \tag{1.1}$$

The rate at which the bits may transmit in the available bandwidth is known as channel capacity. The capacity is the maximum amount of error free bits that can be transmitted over the channel in a given amount of time based on a given bandwidth.

The idea of relay channel is not a new concept, van der Meulen [54, 56], Sato and Cover [12] have published numerous papers in the 1970s regarding relay channels. Van der Meulen recently presented an introductory talk on relay channel for Mathematical Sciences Research Institute (MSRI) at Berkeley in 2006 [55]. Around the time I began my research, Gupta and Kumar formalized an information theoretical method for obtaining an achievable communication rate region in a network with arbitrary size and for arbitrary topology. Their papers, "Toward an Information Theory of Large Networks: An Achievable Rate Region" [18] and "The Capacity of Wireless Networks" [19] suggested that under an interference free model with an N-node network, the scaling law of an ad hoc network has an average throughput approaching zero as the number of nodes increases in the network. Therefore, only small ad hoc networks or networks with nodes

supporting their nearest neighbors during transmission is achievable. To overcome this limitation, one must look upon using multiuser coding schemes. This is perhaps the importance of relay channels and multi-hop wireless networks schemes.

Around the same time Gupta and Kumar's paper was published in 2003, Kramer et al. presented their paper "Capacity Theorems for Wireless Relay Channels" [23] and found an achievable rate region for relay networks in an all white Gaussian channel. Their results agree with Gupta and Kumar in that a multi-hop system achieves information-theoretic capacity of wireless relay network if the relays are near the source terminals and that phase information is available to the receiver for synchronization.

Relay channels, or peer-to-peer routing, is the core of a wired network, yet it does not take advantage of the spatial diversity that is inherent in the broadcast nature of a wireless network. Through cooperation, a network may benefit by relaying messages for other nodes and combat various types of fading or interference. By redundantly transmitting signals via multiple paths in the network, each node has the potential to use a lower transmission power setting for the same performance and avoid less than ideal paths in a rough terrain or noisy environment. An earlier paper by Bergmans and Cover in 1974 derived that cooperative broadcasting (superposition coding) for two transmitters dominates frequency multiplexing or naive time sharing schemes [9]. Bergmans established that the achieved rate with cooperative broadcasting scheme is optimal. Recently, authors from [45, 43, 44] showed a theoretical analysis that cooperation leads to an increase in capacity and system robustness. Spatial diversity can combat signal fading from multi-path propagation and Doppler frequency shift. More attractively, spatial diversity can be combined with time and frequency diversity [20], as signals fade independently in time and space.

In Laneman's dissertation [26], he showed that cooperation yields full spatial diversity and thus allows significant transmit power savings at the same level of outage probability for a transmission rate. His contribution on spatial diversity gained a wide audience and his papers are closely studied for the cooperation case in this dissertation.

A paper on node cooperation would not be complete without mentioning the

significant findings and contributions from Andrea Goldsmith and her students at Stanford University. The group published numerous papers analyzing the benefits of node cooperation [21, 32]. Their paper on two transmitters and two receivers cooperation answered many questions of whether to use receiver cooperation or not. They found that under certain channel conditions, transmitter cooperation is more beneficial than receiver cooperation, and vice versa. They also confirmed that using both types of cooperation provides the best capacity limits. Similarly to most published papers, two-node cooperation is popular and having more than two nodes cooperating together is rare. Perhaps the multiple node cooperation studied in this dissertation could someday gain at least a fraction of attention as Goldsmith's contribution to the world of wireless ad hoc networks.

1.3 Background

1.3.1 Wireless Ad Hoc Networks

Wireless networks have been around since Abramson began testing his ALOHAnet in the late 1960s at the University of Hawaii [1]. His story was honored and retold in the History of Communication section of IEEE Communication Magazine in 2009 [2]. It was only recently that electronic advances enabled designs of infrastructure-less networks. Wireless ad hoc networks are either non-mobile or mobile networks comprised of decentralized nodes without infrastructure. The aim of such networks is to perform tasks based only on the abilities of the participating nodes. This type of infrastructureless network is unique from infrastructure networks in that no prior pre-deployment is necessary and self organized nodes act as both end users and serve as routers. The lack of centrality or base station require all nodes be aware of their immediate surroundings.

The participating nodes in the network must be able to communicate with other nodes or assist in relaying information. A typical ad hoc network employs either single-hop communication between nodes or uses multi-hop communication. Figure 1.1 shows two typical examples of ad hoc networks; (a) is a fully connected network where any

node may communication with any other node in the network via a single hop. (b) is a multi-hop network where at times nodes may need to utilize relay nodes to reach destination nodes that are outside the transmitting nodes' wireless range.

Research areas are broad for wireless ad hoc networks. There are many challenging areas that are currently under study. Some topics of interests are: available energy, processing power, memory and storage, bandwidth and throughput, reliability, deployment, mobility, addressing, scalability, costs, environmental conditions, and miniaturization. While many topics have been studied in depth by researchers, there are still many areas require further exploration. For examples, no concrete network lifetime has been analyzed, robustness and fault tolerance, quality of service, software management, self-organization, data-centric networking, synchronization, and coordination are just a few areas that are still not studied in depth. Although the concept is still relatively new, there are already applications out running or desire of such applications have been voiced. Some applications of wireless ad hoc networks are habitat monitoring, disaster recovery, emergency operation, situation awareness, and logistics tracking. Some examples of wireless ad hoc networks are wireless mesh networks (WMNs), sensor networks (WSNs), and vehicular ad hoc networks (VANET).

The simplest case of ad hoc networks is non mobile. The network is assigned with a fixed unique identifier and required to maintain communication similar to a wired one. Wireless Mesh Network are an example of such a network. In the mobile case, nodes are allowed to move positions over time. Each node must be able to determine the relative location of other nodes in the network and any changes in network topology. One popular application of mobile ad hoc networks (MANETS) is vehicular ad hoc networks, where inter-vehicle communications allow data transfer using a multi-hop network to share information such as road condition and traffic safety. In both non mobile and mobile cases of ad hoc networks, wireless sensor networks are becoming increasingly popular in ad hoc network research. Wireless sensor network is a group of sensor nodes that may or may not be mobile, using wireless radio communication to collect and pass data between nodes and a base station. Sensor network is a type of MANETS which collects data [14].

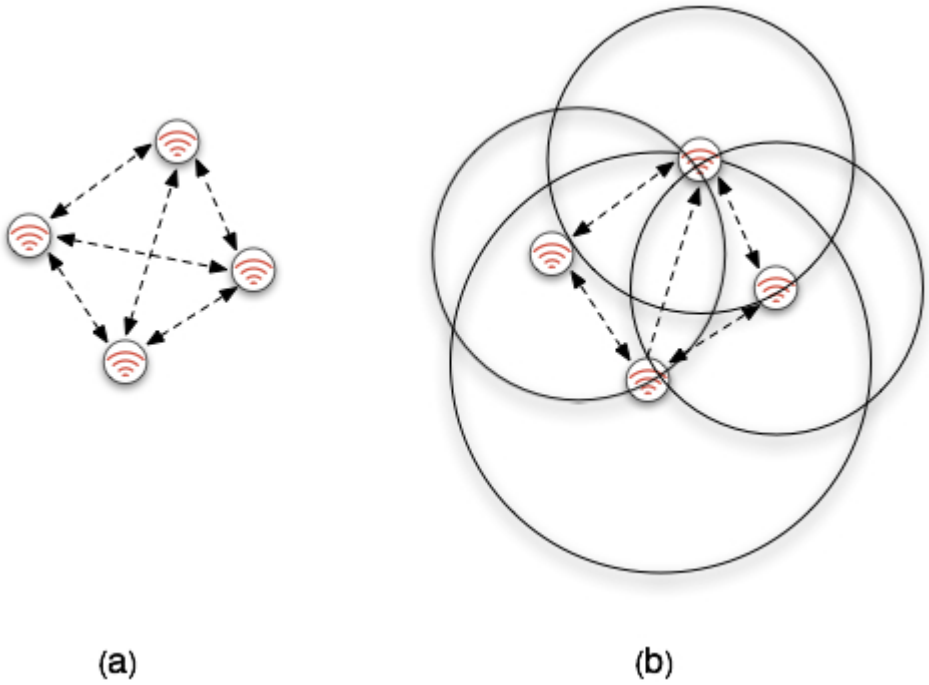

Figure 1.1: Sample traffic flow with only one or two hops considered, (a) direct hop, (b) multi-hop. Multi-hop is necessary in some cases because the transmission range of a node (indicated by a solid circle around the node) falls short of reaching the destination.

1.3.2 Understanding Capacity and Shannon Theorem

Claude E. Shannon established a theory stating that for a communication channel, one could bound the maximum amount of error-free bits that can be transmitted over a noisy environment under a specified bandwidth. This rate is the channel capacity that presents the theoretical tightest upper bound on the rate with no error coding used. Suppose there exists a communication channel which can transmit R number of binary digits, error free, in one second, and each binary digit contains an information bit. Then, this communication channel is said to have channel capacity of R bits per second. Considering again if a source is said to have entropy of H bits per symbol, then the source may on average, transmit at a rate of $\frac{R}{H}$. If for any reason H is greater than R, then the rate of transmission is greater than the channel capacity and the information bit would not be transmitted error-free [36].

Dr. Dohler's dissertation [13] expertly described Shannon's work on channel

capacity in the Gaussian case. It is simplified further to serve as a background for this dissertation. Given entropy $H(x)$ as described by a continuous random variable x with probability density function $pdf(x)$ as described by Shannon,

$$H(x) \equiv -\int pdf(x) log_2(pdf(x)) dx. \tag{1.2}$$

The random variable x is of Gaussian distribution with mean μ and variance σ^2, the entropy is calculated to be

$$H(x) = \frac{1}{2}\log_2(2\pi e\sigma^2), \tag{1.3}$$

where e is the natural constant. If y is observed as the received signal of x being transmitted and observing y removes all uncertainty over x, then the mutual information is equal to the entropy of $H(x)$ and the channel capacity is the maximum mutual information over all possible $pdf(x)$. Given x is transmitted over an additive white Gaussian noise channel with noise n, the received signal is then defined as $y = x + n$. With S being the average power of the signal and N is the average power of noise:

$$C = \frac{1}{2}\log_2\left(\frac{S+N}{N}\right) = \frac{1}{2}\log_2\left(1+\frac{S}{N}\right). \tag{1.4}$$

Signals are normally transmitted during a period of T and limited to bandwidth W. Thus, the capacity of a band limited signal is

$$C = WT\log_2\left(1+\frac{S}{N}\right). \tag{1.5}$$

The channel capacity is described in bits per second, where W is the channel's bandwidth in hertz, S is the received signal power over the bandwidth and N is the noise power over the bandwidth. $\frac{S}{N}$ is the signal to noise ratio (SNR) in linear scale.

1.3.3 Wireless Channel Impairments

In simulation, it is important to capture the effects of the wireless channels on signals being transmitted. Unlike wired medium, wireless medium can be unstable and faces interference due to uncontrollable factors unrelated to the network. The impairments described in this section is propagation impairments, caused by path loss and different types of fading.

Path loss is the attenuation of signal power as the signal propagates through a medium. The common medium is air but could also be other materials. For each decade of increase of distance between transmitter and receiver in a perfect vacuum, there is a path loss of 20dB, while it takes twice as many transmitters cooperatively send together to obtain a 3dB gain in signal strength. Therefore, path loss is a major impairment in communication. Path loss is normally expressed as decibel scale:

$$L = 10\gamma \log_{10}(d), \tag{1.6}$$

where L is the path loss, γ is the path loss exponent, and d is the distance between the transmitter and receiver. For this dissertation, d is of unity to obtain results in normalized signal-to-noise ratio, and the distance between nodes is represented by R. Thus if the distance between node i and node j is $R_{i,j}$, with path loss exponent being 4 for lossy medium, the path loss is defined as:

$$L = 10(4) \log_{10}\left(\frac{d}{R_{i,j}}\right), \tag{1.7}$$

or

$$10^{\frac{L}{10}} = \left(\frac{d}{R_{i,j}}\right)^4, \tag{1.8}$$

in linear scale.

Besides path loss, multi-path fading and shadow fading are also considered into the model. Multi-path described the signal traveling along different paths to the re-

ceiver. This could potentially increase or decrease the quality of the signal arriving at the receiver as the signal may constructive or destructive affect the same signal arriving at different paths. This is a natural propagation phenomenon that is existing in wireless communications, but its effect on the overall network throughput is relatively small when compared to path loss. Here, multi-path fading is represented by an exponentially distributed random variable drawn independently for each transmit and receive pair.

Finally, the propagation impairments may also consist of shadow fading. Shadow fading is a deviation of the attenuation that a signal experiences over the transmission channel. This is normally caused by obstacles affecting the propagation and results in loss of signal power. Spatial diversity is a common way to combat shadow fading because it is unlikely that multiple channels face the same physical obstacles. Here, shadow fading is represented by a zero mean Gaussian random variable with standard deviation of six, drawn independently for each transmit/receive pair.

1.3.4 Spatial Diversity and Cooperative Diversity

Even though multi-path fading is a natural propagation phenomenon, it is possible to combat such fading using spatial diversity. Spatial diversity is the case where the signal is transferred over different propagation paths to take advantage that fading varies for different paths. This is usually achieved by employing multiple antennas at a quarter of the wavelength apart to achieve uncorrelated channels. However, having a small mobile node installed with multiple antennas is not practical. Therefore, spatial diversity can be achieved by allowing nodes cooperatively transit together. In a conventional system, a receiver accepts only the signal from the source and regard other signals as interference. However, if the receiver decodes the signal from secondary sources and combines the information with the signal from a direct source, it is then taking advantage of spatial diversity by using antennas from multiple nodes within the network, which is commonly known as cooperative diversity.

1.4 Aims and Organization of the Dissertation

Designs of wireless networks is particularly challenging because of the nature of the medium the signals must travel through, unlike in a wired network. Researchers face challenges with path loss, multi-path fading, shadow fading, and possible interference from other nodes. The simple answer might be to increase transmission power, but this might be self-destructive for a network because of the increased amount of interference and shorter lifetime for the nodes. In some cases, such as a network setup in a rough terrain, replacing the batteries for nodes might not be feasible. The nodes must preserve what little resources they have.

While capacity limits have nearly reached their limits for a peer-to-peer hop-by-hop system, there are still unchartered regions for ad hoc networks to act cooperatively, in order to exploit the nature of broadcasting and to take advantage of cooperative diversity. The capacity limitation of current wireless networks have not been fully optimized with current technology.

This dissertation is dedicated to determining capacity limits for node cooperation. First, this dissertation determines a metric in which all progresses are to be compared against. This metric is based on a peer-to-peer, hop-by-hop routing with frequency reuse, using information theory on a switching network. Since this bound is the best possible bound that is not achievable in the physical world, it is a difficult bound to outperform. The best-case scenario would be if node cooperation could outperform this optimistic upper bound. Next, this dissertation determines the benefits of node cooperation and the total capacity of any given network with randomly distributed nodes in a service area. A predefined capacity matrix is presented indicating the capacity links between nodes with the effects of path loss, multi-path fading, and shadow fading. The node cooperation is then extended beyond paired nodes cooperation, up to six nodes cooperation. Finally, the naive time-share bound is rejected and frequency reuse bound is calculated to determine how close this capacity bound is to the initial metric.

Chapter 2 presents the network model used by all three bounds with some alter-

ations for the frequency reuse case. Chapter 3 presents the information theoretic upper bound for a peer-to-peer hop-by-hop wireless ad hoc network. While the upper bound is easily scalable and not achievable in the physical world, it serves as a yard stick for the work presented in chapters 4 and 5.

The lower bound with node cooperation without frequency reuse is the beginning of our study on node-cooperation. Chapter 4 focuses on transmitter cooperation with two, three, or more nodes. This bound is derived from a simple time-share bound in which no frequency reuse is allowed. Therefore, only one node or group of cooperating nodes are allowed to transmit at any given time. This bound is simple and while excellent results are not expected, it is a starting point for further analysis.

Chapter 5 is built from the study presented in chapter 4 where the model is without frequency reuse. Frequency reuse creates interferences among nodes and therefore more difficult to add to the simulation and determine the network capacity. To ensure convergency, the optimal path determined in chapter 4 is used, where the paths are based on nodes transmitting at the same time creating the least impact on the capacity links of the other transmitting nodes. This method creates a scenario where nodes are sending similar to an interference-free environment.

Chapter 6 is the last chapter of this dissertation. It summaries the contributions of this dissertation and provides possible improvements and potential future directions.

The analysis in this dissertation is done on a static network, or a snapshot in time. This is because in most scenarios nodes do not cover significant distances in a short duration of time.

1.5 Contributions

In this dissertation, three capacity bounds of wireless ad hoc networks with a given set of network parameters are analyzed. First, the information theoretical upper bound for a peer-to-peer wireless ad hoc network with hop-by-hop routing is produced. This upper bound is an optimistic upper bound that is unachievable in the real world.

However, this bound serves as an important measure against the results from the simulated lower bounds with node cooperation. Different traffic patterns are also imposed on the simulated results to understand the network behavior given certain amount of destination uncertainty. Then, a bottleneck is introduced to the network in which all traffic must transmit to three and five relay nodes that have access to the base station (or destination). This result closely relates to the popular mesh network.

Literature states that adding spatial diversity enables better network performance. The results of the lower bounds in this dissertation support this findings because the paired nodes cooperation has a higher overall network throughput than the peer-to-peer routing with the same simulation settings. However, this benefit diminishes as the SNR increases.

Chapter 2

Network Model

Given a set of N nodes in a network, this network is characterized by two N by N matrices. Given the available power at each node, the physical separation between nodes, and the channel impairments between each pair of transmitting and receiving nodes, each element of the capacity matrix represents the maximum rate at which information may be transferred in the absence of co-channel interference. Each element of the relative traffic matrix represents the relative exogenous demand existing between a pair of nodes.

All bounds are calculated based on these two matrices with the final results in terms of normalized SNR versus bits per second per hertz for ease of comparison. To do so, the bandwidth is set to one and the service area is represented by a square grid in which the nodes are distance d apart:

$$d = \frac{L}{\sqrt{N} - 1}, \tag{2.1}$$

where L is the length of each side of the service area and d is one. The grid is divided by horizontal and vertical lines separated by distance d. Suppose that the nodes are placed at the intersections, then in the absence of fading and interference, the SNR observed at the receiving nodes would be normalized SNR between any two adjacent nodes. Figure 2.1 shows a sample grid of a service area where nodes are spread at a fixed distance d apart.

If the nodes are randomly placed on a service region, to obtain the same normalized SNR between two adjacent nodes, the SNR is scaled accordingly based on the distance.

To determine the capacity matrix, first assume each node is constrained to P watts of power for transmission. If the noise level at the receiver is known, it is possible to define the interference-free signal-to-noise ratio (SNR) as observed at the receiving nodes when only one sending node is transmitting in the network. Then, assume the total channel bandwidth is W, the maximum rate at which information can be sent between the transmitter and receiver pair is given by the Shannon limit:

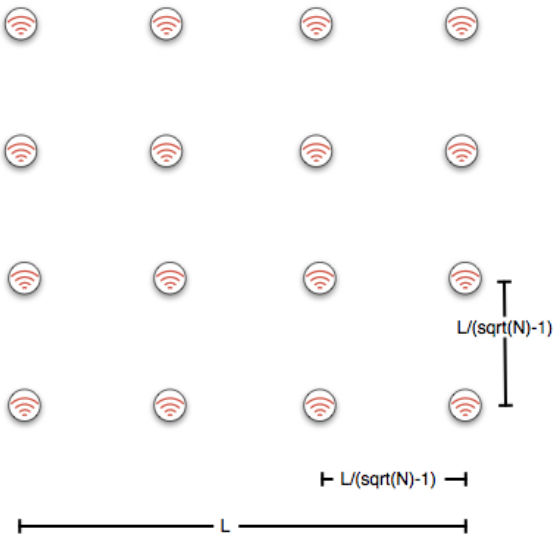

Figure 2.1: Sample placement of nodes on an uniform grid

$$C = W \log_2(1 + SNR). \tag{2.2}$$

The link capacity matrix represents the point-to-point Shannon capacity between node i and j. It is calculated based on interference-free SNR produced when node i is sending at its maximum allowable power to node j. Repeating equation 2.2 above for each N by $N-1$ transmitting and receiving pairs, the interference free link capacity matrix is defined as follows:

$$C = \begin{bmatrix} C_{1,1} & C_{1,2} & \dots & C_{1,N} \\ C_{2,1} & C_{2,2} & & C_{2,N} \\ \vdots & & \ddots & \vdots \\ C_{N,1} & C_{N,2} & & C_{N,N} \end{bmatrix}, C_{i,j} = 0, \forall i = j. \tag{2.3}$$

The main diagonal is zero because nodes do not send packets to themselves. The path loss from node i to node j is the same as from node j to node i. Therefore, the capacity matrix is symmetrical.

In the case where multiple nodes are sending simultaneously, the above capacity matrix no longer holds. Interference must be accounted for in equation 2.2. The

derivation to account for frequency reuse is given later in this dissertation.

All simulations performed in this dissertation include a propagation model. This model includes channel impairments such as path loss, multi-path fading, and shadow fading between each node. The equation for path loss is defined as

$$r = \left(\frac{d}{R}\right)^4, \tag{2.4}$$

where d is defined earlier by equation 2.1. R is the distance between two nodes in the square service area. The power of four is for modeling metropolitan area, where nodes are sending in a relatively lossy environment.

The multi-path fading is exponentially distributed with a random variable X and a mean of one. From the experimental data, multi-path fading has very little effect on the overall impact when path loss is present because path loss has a higher order of magnitude than multi-path fading. Finally, the shadowing fading uses a log normal distribution with standard deviation of 6 dB.

Thus, incorporating path loss, multi-path fading, and shadow fading, the SNR between each node is adjusted,

$$\rho_{i,j} = \rho \left(\frac{d}{R}\right)^4 e^X 10^{\frac{\epsilon}{10}}, \tag{2.5}$$

where ρ is the impairment free SNR in linear scale and ϵ is Gaussian distributed, zero mean with standard deviation of 6 dB. $\rho_{i,j}$ is the SNR from node i to node j. Using this SNR with impairments to fill in the capacity matrix with normalized bandwidth using Shannon capacity from equation 2.2,

$$C = \log_2(1 + \rho_{i,j}). \tag{2.6}$$

The traffic matrix consists of element $t_{i,j}$. Each element represents the exogenous traffic from source node i to the destination node j in packets per second where each packet contains a fixed number of bits. The upper bound scheme seeks to maximize the

scaling factor K such that the relative traffic matrix is at its maximum based on link capacity. Any increase in traffic would cause the network to lose packets because the traffic is greater than the channel capacity.

The relative traffic matrix is defined as follows:

$$T = \begin{bmatrix} t_{1,1} & t_{1,2} & \dots & t_{1,N} \\ t_{2,1} & t_{2,2} & & t_{2,N} \\ \vdots & & \ddots & \vdots \\ t_{N,1} & t_{N,2} & \dots & t_{N,N} \end{bmatrix}, t_{i,j} = 0, \forall i = j. \tag{2.7}$$

The elements of the traffic matrix's main diagonal are zero because nodes do not send packets to themselves. However, there is no reason that the traffic matrix must be symmetrical, as some clients may exist on different workstations or servers.

Chapter 3

Information Theoretical Upper Bound

3.1 Introduction

The past decade experienced an explosion of interest in the field of wireless communications. Researchers have shifted focus toward mobile ad hoc networks from conventional infrastructure wireless networks such as cellular networks and wireless local area network based on the 802.11 standard. Some effort has focused on the more limited subspace of peer-to-peer wireless networks where wireless nodes organize themselves into networks for the purpose of passing information between nodes. The potential to extend the range beyond which the infrastructure networks can reach, the potential for application to sensor networks, the flexibility of node deployment in rough terrains, the possibility of an alternative to installing infrastructure for networks deployed on a temporary basis, the potential for extending the range of each access point of an infrastructure network, and the possibility of using peer-to-peer nodes to provide service to mobile stations and to communicate amongst themselves to create a mesh-based backhaul network are just a few examples why ad hoc networks are gaining popularity. In some cases, it is too costly and inconvenient to set up an infrastructure network in rural areas. A real life example of deploying a wireless sensor network is described by the authors in [50] and the challenges of deploying a hybrid model is described in [10]. Both groups of researchers described their experience in deploying wireless sensor networks in a marine environment.

There are a number of issues needed to be addressed with wireless ad hoc networks that are not real issues with conventional infrastructure wireless networks. By virtue of the broadcast nature of radio communications, an N node peer-to-peer wireless network may be viewed as a set of N fully connected network. However, the transmit power available to each node, the physical separation between node pairs, propagation impairments, and co-channel interference caused by concurrent transmission will limit the rate at which information may be sent from one node to another via a direct link. Mutihopping must be performed among nodes to overcome the absence of full connectivity in the case of failed links or nodes. The lack of a centralized base station also introduces

complications. There is no base station to address the transmission resources, synchronization, delay, and path discovery. Ad hoc networks must be able to self-organize and identify the topology to maintain their wireless connections. Nodes must maintain at the very least local awareness by periodically updating neighboring nodes. Such updates require bandwidth as well as using the node's limited power capacity. Many researchers have placed their focus on energy efficiency [22, 25] because the lifetime of a node is of utmost importance; the use of a network ends when nodes are out of power, and replacing the batteries of the nodes may not be an option in some cases. Other researchers have placed their focus in categories such as scalability [37, 11, 29], quality of service (QoS) [48], bandwidth allocation [48], network security [33, 58], load balancing, and routing protocols [51, 30, 16, 28, 34, 35, 24, 40, 38]. There are also a few excellent papers that focus on the capacity of a network [15, 29, 52]. The authors of [29] showed that for the total capacity to scale as the network increases in size, the average distance between the source and destination nodes must remain small. They experimented with simple configurations and different traffic configurations. Although their paper resembles the research presented in this dissertation, they haven't determined the upper bound by applying information theory on switching networks. This work is based on Acampora's previous study on information-theoretic bound for the capacity of multi-hop lightwave networks [3]. This dissertation uses a relatively simple model to calculate results in comparison to Tan's flow deviation method [49, 7]. Tan's method is more rigorous but it is not scalable to a large network. Furthermore, this dissertation uses static networks for all analysis similar to the authors of [29] did to analyze the capacity of the network. This is a valid restriction because mobile nodes do not tend to cover significant distances in a short duration of time.

Consider a network of N nodes in which each node may wirelessly communicate among themselves in peer-to-peer fashion. Each node may send information to any node in the network except to itself in a single hop or route traffic among nodes in a conventional hop-by-hop fashion. This chapter considers the fundamental upper bound for such a network. This bound is not practical since no wireless ad hoc networks using

the conventional hop-by-hop fashion can produce such throughput. However, this bound does provide an important yardstick for future work with node cooperation.

The network of interest is characterized by two N by N matrices. The available power at each node, the physical separation between nodes and the propagation impairments between each pair of nodes is predefined. Start with two predefined inputs in calculating the upper bound; the link capacity matrix and the relative traffic matrix. Each element of the capacity matrix represents the maximum rate that information can be transferred between a pair of nodes in the absence of co-channel interference. Although the N-node network is fully connected, the elements of the capacity matrix will vary over a wide dynamic range because not all links undergo the same amount of propagation impairments. Each element of the relative traffic matrix represents the relative exogenous demand that exists between a pair of source and destination nodes. The object is to determine the maximum scaling factor by which the traffic matrix can be scaled such that the resulting traffic can be carried by the network.

To obtain this bound, the well known information theoretic concept is applied to the switching network instead of the physical links. The result is an easily computed upper bound that is not as accurate as using the conventional method of flow deviation, but this bound can be scaled and applied to arbitrarily large networks. This bound, however, considers only the inherent destination uncertainty of the exogenous traffic and the maximum rate at which switching decisions can be made by N nodes when the node-to-node transmission rates are limited by the elements in the capacity matrix. This upper bound is generated by ignoring the effects of interference caused by concurrent transmission. The rate at which a transmitting and receiving pair of nodes may communicate is interference-free Shannon capacity of that link, that no resources are needed for path discovery nor localization, and that the total number of switching decisions can not possibly be greater than the calculated value scaling the traffic matrix. This bound, however, does have a set of constraints. Each node is subject to the requirements listed:

1. A node may not transmit to more than one intended receiver at a time.

2. A node may not accept multi-hop traffic from more than one transmitter at a time.

3. A node may not transmit and receive simultaneously.

Based on these restrictions, it is possible to bound the maximum number of routing decisions per unit time that each node can perform based on the capacity matrix. Using the relative traffic matrix, one may define the source switching entropy, corresponding to the destination uncertainty of the arriving traffic. Next, summing the maximum number of routing decisions per unit time over all nodes and equating the result to the source switching entropy, determine the upper bound for the maximum factor K that the relative traffic matrix may be scaled. For this relative traffic matrix, no connectivity pattern or routing algorithm can provide a higher absolute throughput.

For the remainder of this chapter, the scaling factor will be covered first. Derivation is provided in determining K such that if the relative traffic matrix is scaled by a value greater than K, the network could not possibly transmit all bits error free. Next, the switching network is covered, which is the maximum rate at which binary switching decisions can be made by a network of N peer-to-peer nodes is derived. Then, the scaling factor is used to determine the capacity of a network. Finally, results and conclusions are presented at the end. All results are presented in terms of maximum possible network throughput as a function of the interference-free SNR between a pair of distance-normalized source and destination nodes.

3.2 Scaling Factor

The objective is to determine the maximum value of K, a scaling constant, such that the relative traffic matrix is at its maximum based on link capacity. With this K, no connectivity or flow solution can possibly produce a higher throughput. This bound does not require that the optimized connectivity and flow be found. To compute the highest possible throughput for a relative traffic matrix, an easily computable constraint is applied on the maximum rate at which switching decisions can be made by network nodes for any connectivity and flow. There is a maximum rate at which switching

decisions can be made by each node follows from the fact that each link leading from a node has an associated maximum data rate. Instead of trying to optimize the flow for a given relative traffic matrix, the traffic matrix is scaled by increasingly larger values of K, the switching rate needed will eventually exceed the maximum rate at which the nodes can perform switching decisions. If each element of the traffic matrix is scaled by a value greater than K, then it would be impossible for the network to deliver all the traffic without dropping packets. Summing up all the traffic elements and scaling by K gives the maximum throughput of the network:

$$S = K \sum_{i=1}^{N} \sum_{j=1}^{N} t_{i,j}. \tag{3.1}$$

To find the upper bound, first determine the maximum rate at which switching decisions can be made by the network and compare it to the rate at which decisions must be made. To determine the maximum rate at which switching decisions can be made by the network, define the entropy of the traffic matrix. Consider the i^{th} network node. The user attached to this node generates exogenous packets to the user attached to the j^{th} node. The total relative traffic at which the user attached to i^{th} node generates packets for any of the $N-1$ nodes in the network can be expressed as:

$$R_i = \sum_{l=1, l \neq i}^{N} t_{i,l}. \tag{3.2}$$

Therefore, the probability of an exogenous packet generated by a user at node i intended for the user at node j is given by:

$$r_{i,j} = \frac{t_{i,j}}{R_i} = \frac{t_{i,j}}{\sum_{l=1, l \neq i}^{N-1} t_{i,l}}. \tag{3.3}$$

The entropy of the user attached at the i^{th} node is the minimum number of bits of routing information required on average to identify the destination. The entropy of the user attached at node i is given by:

$$\epsilon_i = -\sum_{j=1}^{N} r_{i,j} \log_2 r_{i,j}. \tag{3.4}$$

The absolute traffic can be scaled by K, while the absolute rate at which the user from node i generates exogenous traffic is given by KR_i. Thus, the minimum rate at which the user generates routing bits of information is:

$$B_i = KR_i\epsilon_i = -K\left(\sum_{l=1,l\neq i}^{N} t_{i,l}\right)\sum_{j=1}^{N} r_{i,j} \log_2 r_{i,j}, \tag{3.5}$$

substituting $r_{i,j}$ using equation 3.3 and where,

$$\sum_{l=1,l\neq i}^{N-1} t_{i,l} = \sum_{l=1}^{N} t_{i,l}, \tag{3.6}$$

because all traffic elements from the main diagonal of the traffic matrix are always zero:

$$B_i = -K\sum_{l=1}^{N} t_{i,l}\sum_{j=1}^{N}\left(\frac{t_{i,j}}{\sum_{l=1}^{N} t_{i,l}}\right)\log_2\left(\frac{t_{i,j}}{\sum_{l=1}^{N} t_{i,l}}\right), \tag{3.7}$$

simplifying to:

$$B_i = K\sum_{j=1}^{N} t_{i,j}\left[\log_2\left(\sum_{l=1}^{N} t_{i,l}\right) - \log_2 t_{i,j}\right]. \tag{3.8}$$

By summing all N users, the total minimum rate at which routing bits of information is generated can be expressed as:

$$B = \sum_{i=1}^{N} B_i \tag{3.9}$$

$$= K\sum_{i=1}^{N}\sum_{j=1}^{N} t_{i,j}\left[\log_2\left(\sum_{l=1}^{N} t_{i,l}\right) - \log_2 t_{i,j}\right]$$

.

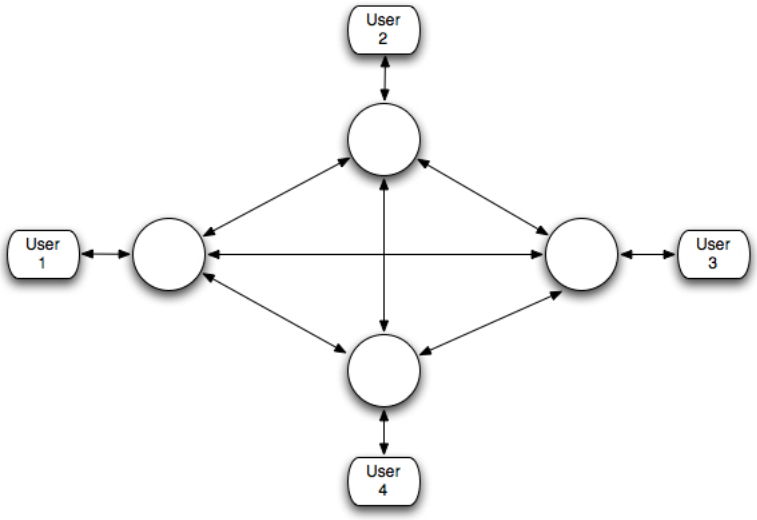

Figure 3.1: Sample 4-node fully connected network.

3.3 Switching Model

Figure 3.1 shows a fully connected network consisting of four nodes. A node may receive a packet from any node in the network except from itself and the maximum rate at which information may arrive from another node is the interference-free Shannon limit. Such a packet is not an exogenous packet but a multi-hop packet because the node simply relays the packet. An exogenous packet may also arrive from an attached user and a packet may be transmitted from node i to another network node at the maximum rate. This packet transmitted from node i to another node could be either an exogenous packet or a multi-hop packet. An exogenous packet is when a packet was generated by a user attached to node i, whereas a multi-hop packet is when it arrives at node i from another node. If a packet arrives at node i from another node that is intended for the user at node i, then the packet would be delivered to the user rather than be relayed or multi-hopped to another node.

In this hop-by-hop scenario, the following three wireless network constraints apply at any given time:

1. No node can receive a packet from more than one transmitting node.

2. No node can send a packet to more than one receiving node.

3. No node can send and receive simultaneously.

Suppose each fixed length packet contains M bits. If a packet is sent from node i to node j, the minimum time needed to transmit a packet is given by the number of bits divided by the respective capacity link:

$$\tau_{i,j} = \frac{M}{C_{i,j}}. \tag{3.10}$$

To upper bound the rate at which packet switching decisions can be made by the i^{th} network node assumes that any packets arriving at node i from another node transmits with the highest capacity, or $C_{max,i}$. All packets relaying to node i by any other node are assumed to arrive at the maximum data rate of the respective capacity link. If node i is to relay the packet to another node, the packet will be transmitted by the capacity link between the transmit/receive pair. For example, for node i to transmit to node k, the data rate is given by $C_{i,k}$. A time sequence of activity over the radio interface at node i can contain (1) traffic generated by the user attached at node i, (2) fixed length time interval in which a fixed length packet arrives at node i over the radio interface, and (3) fixed length packet is send from node i to the channel. The time consumed by the transmission on the channel is inversely proportional to the capacity link.

The time needed to receive a fixed length packet containing M bits from the user at node i, delivering to node j is given by:

$$\tau_{User,i} = \frac{M}{C_{max,i}}, \tag{3.11}$$

where the maximum link capacity is used for any packets generated by the user at that node. The radio time needed to send a fixed length packet containing M bits generated by the user at node i that transmits to node j is given by:

$$\tau_{i,j}^{User} = \frac{M}{C_{i,j}}. \tag{3.12}$$

Therefore, node i is either receiving a relayed packet from another node at the maximum rate, or transmitting to another node at the corresponding rate defined in the capacity matrix. The total radio time plus transmit time needed to relay a fixed length packet containing M bits from node i to j is given by:

$$\tau_{i,j}^{Total} = \frac{M}{C_{max,i}} + \frac{M}{C_{i,j}}. \tag{3.13}$$

The probability that a packet arriving at node i to be relayed to another node in the network is $p_{i,j}$, where $j = 1, 2, ..., N; j \neq i$. $p_{i,u}$ is the probability that a packet arriving at node i is intended for the user attached at node i. $q_{i,j}$ is the probability that a packet generated by the user at node i is to be relayed to node j, where $j = 1, 2, ..., N; j \neq i$. The probability in the case of traffic arriving at node i for either relay or for the user attached to node i must sum to one:

$$\sum_{j=1, j\neq i}^{N} p_{i,j} + p_{i,u} = 1. \tag{3.14}$$

Similarly, the probability that a packet generated by the user at node i to be relayed to other nodes in the network must also be equal to one, because all packets must be transmitted:

$$\sum_{j=1, j\neq i}^{N} q_{i,j} = 1. \tag{3.15}$$

Information theory states that the minimum number of switching information bits that must be processed by node i to correctly deliver a packet to the next-hop node j for relay is given by:

$$-\log_2(p_{i,j}). \tag{3.16}$$

or to the user at node i:

$$-\log_2(p_{i,u}). \tag{3.17}$$

The minimum number of switching information bits that must be processed by node i to correctly deliver a packet to node j is given by:

$$-\log_2(q_{i,j}). \tag{3.18}$$

To find the upper bound, it is necessary to optimize the values $p_{i,j}$ and $p_{i,u}$ such that the number of switching decisions per unit time is maximized. The same process is also applicable to $q_{i,j}$.

The average rate that switching decisions can be made by node i for a fixed length packet arriving at a receiver is given by:

$$R_j^{Radio} = -\left[\sum_{j=1,j\neq i,}^{N} \frac{p_{i,j}\log_2 p_{i,j}}{\left(\frac{M}{C_{max,i}}+\frac{M}{C_{i,j}}\right)}\right] - \frac{p_{i,u}\log_2 p_{i,u}}{\left(\frac{M}{c_{max,i}}\right)} \tag{3.19}$$

and the average rate that switching decisions can be made by node i for a fixed length packet generated by the user at node i is given by:

$$R_i^{User} = -\sum_{j=1,j\neq i}^{N} \frac{q_{i,j}\log_2 q_{i,j}}{\left(\frac{M}{C_{i,j}}\right)}. \tag{3.20}$$

If switching decisions are made between packets arriving at the receiver occurs for a fraction of time f and packets generated by the user for transmission occurs for a fraction of time $1-f$, the rate at which switching decisions are made by node i is given as:

$$R_i = fR_i^{Radio} + (1-f)R_i^{User}. \tag{3.21}$$

The goal is to maximize the rate with respect to $p_{i,j}$, $j = 1, 2, ..., N$, and $q_{i,j}$, $j = 1, 2, ..., N$. When maximized with respect to the $p_{i,j}$, R^{Radio} is larger than $R^{User}$when

maximized with respect to $q_{i,j}$, then R_j is maximized by choosing $f = 1$, else $f = 0$ should be chosen. To accomplish this, maximize R^{Radio} and R^{User} separately and choose the larger.

From equation 3.19, first simplify $\frac{M}{C_{max,i}} + \frac{M}{C_{i,j}}$ to $\frac{M(C_{max,i}+C_{i,j})}{C_{max,i}C_{i,j}}$ and move M outside the summation. Then apply LaGrange multiplier to maximize R^{Radio},

$$R_i^{Radio} = -\frac{1}{M}\sum_{j=1,j\neq i}^{N} \frac{C_{max,i}C_{i,j}}{C_{max,i}+C_{i,j}} p_{i,j}\log_2 p_{i,j} - \left(\frac{C_{max,i}}{M}\right) p_{i,u}\log_2 p_{i,u}$$

$$+\frac{\lambda}{M}\sum_{j=1,j\neq i}^{N} p_{i,j} + \frac{\lambda}{M}p_{i,u} - \frac{\lambda}{M} \tag{3.22}$$

and take the partial derivative with respect to $\partial p_{i,j}$:

$$\frac{\partial R_i^{Radio}}{\partial p_{i,j}} = -\frac{1}{M}\left[\frac{C_{max,i}C_{i,j}}{C_{max,i}+C_{i,j}}\right](1+\log_2 p_{i,j}) + \frac{\lambda}{M},\ j = 1,2,...,N; j \neq i \tag{3.23}$$

$$\frac{\partial R_i^{Radio}}{\partial p_{i,u}} = -\left(\frac{C_{max,i}}{M}\right)(1+\log_2 p_{i,u}) + \frac{\lambda}{M}. \tag{3.24}$$

Next, find the optimizing probability distribution by setting the derivatives equal to zero:

$$\frac{\partial R_i^{Radio}}{\partial p_{i,j}} = 0, \tag{3.25}$$

which reduces to:

$$\lambda = \left[\frac{C_{max,i}C_{i,j}}{C_{max,i}+C_{i,j}}\right](1+\log_2 p_{i,j}), \tag{3.26}$$

solving for $P_{i,j}$,

$$\log_2 p_{i,j} = \frac{\lambda - C_{i,j}}{C_{i,j}}, \tag{3.27}$$

$$p_{i,j} = 2^{\left(\frac{\lambda - C_{i,j}}{C_{i,j}}\right)}, \tag{3.28}$$

or

$$p_{i,j} = 2^{\left(\frac{\lambda}{C_{i,j}} - 1\right)}, \tag{3.29}$$

and simplifying further:

$$p_{i,j} = \left[\frac{1}{2}\right] 2^{\frac{\lambda}{C_{i,j}^{eq}}}, \tag{3.30}$$

where

$$C_{i,j}^{eq} = \frac{C_{max,i} C_{i,j}}{C_{max,i} + C_{i,j}}. \tag{3.31}$$

Repeat the steps from equation 3.27 to equation 3.30 in order to find the optimizing probability for when the packets are generated by the user for transmission:

$$\frac{\partial R_i^{Radio}}{\partial p_{i,u}} = 0, \tag{3.32}$$

$$\lambda = C_{i,u} \left(1 + \log_2 p_{i,u}\right), \tag{3.33}$$

$$p_{i,u} = \left[\frac{1}{2}\right] 2^{\frac{\lambda}{C_{i,u}}}. \tag{3.34}$$

The sum of the probability must be equal to one, thus we can find λ:

$$\left(\sum_{j=1, j\neq i}^{N} 2^{\frac{\lambda}{C_{i,j}^{eq}}} \right) + 2^{\frac{\lambda}{C_{i,u}}} = 2. \tag{3.35}$$

Apply the same steps for $p_{i,j}$ and $p_{i,u}$ to find $q_{i,j}$:

$$q_{i,j} = \left[\frac{1}{2}\right] 2^{\frac{\lambda}{C_{i,j}}},\ j = 1, 2, ..., N; j \neq i, \tag{3.36}$$

where

$$\sum_{j=1,j\neq i}^{N} 2^{\frac{\lambda}{C_{i,j}}} = 2. \tag{3.37}$$

Finally, numerically solve for λ and use it to find the optimizing values for $p_{i,j}$ and $q_{i,j}$ to calculate the maximum value for R^{Radio} and R^{User}. The larger of the two is the maximum rate that binary switching decisions can be made by node i. Let D_i represent the largest value in terms of switching bits per second. Summing all nodes in the network, the maximum rate at which binary switching decisions can be made by the network of N peer-to-peer nodes is given by:

$$D = \sum_{i=1}^{N} D_i. \tag{3.38}$$

3.4 Maximum Scaling Factor and Network Capacity

Recall that the scaling factor K scales the traffic matrix such that no connectivity pattern or routing algorithm can provide a higher absolute throughput. By comparing the rate switching decisions must be made by the network against the maximum rate at which the network can make routing decisions, K is calculated by combining equations 3.2 and 3.38:

$$K \leq \frac{D}{\sum_{i=1}^{N}\sum_{j=1}^{N} t_{i,j}\left[\log_2\left(\sum_{l=1}^{N} t_{i,l}\right) - \log_2 t_{i,j}\right]}. \tag{3.39}$$

Therefore, the maximum rate at which fixed length packets can be switched by the network is:

$$F = K\sum_{i=1}^{N}\sum_{j=1}^{N} t_{i,j} \tag{3.40}$$

$$\leq \frac{D\sum_{i=1}^{N}\sum_{j=1}^{N} t_{i,j}}{\sum_{i=1}^{N}\sum_{j=1}^{N} t_{i,j}\left[\log_2\left(\sum_{l=1}^{N} t_{i,l}\right) - \log_2 t_{i,j}\right]}.$$

To obtain the capacity of the network with respect to the relative traffic matrix in bits per second in terms of hertz, multiply the maximum rate of the network by the ratio of the number of bits per packets per hertz. Given that M is the fixed length packet and W is the bandwidth:

$$C \leq \frac{DM}{W} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} t_{i,j}}{\sum_{j=1}^{N} \sum_{j=1}^{N} t_{i,j} \left[\log_2 \left(\sum_{l=1}^{N} t_{i,l} \right) \right]}. \tag{3.41}$$

3.5 Simulation Results

3.5.1 Observations: Uniform Traffic

To examine the network capacity for various relative traffic matrix models, first assume N nodes are randomly and uniformly distributed over a square service area with each side of dimension L as defined in chapter 2.

The propagation model assumes a path loss of $\frac{1}{r^4}$ with flat multi-path fading and with or without shadow fading. The shadow fading is modeled as log normal with standard deviation of six decibels. Then randomly place the nodes over the service area and compute the actual SNR between two nodes in the absence of interference and without shadow fading:

$$\rho(i,j) = \rho W(i,j) \left[\frac{d}{r(i,j)} \right]^4 \tag{3.42}$$

with shadow fading:

$$\rho(i,j) = \rho W(i,j) \left[\frac{d}{r(i,j)} \right]^4 10^{\frac{\epsilon(i,j)}{10}}, \tag{3.43}$$

where:

$r(i,j)$ is the distance between node i and j

$W(i,j)$ is an exponentially distributed random variable drawn independently for each (i,j) pair for multi-path fading

$\epsilon(i,j)$ is a lognormal distributed random variable with a standard deviation of

six drawn independently for each (i,j) for shadow fading.

Three types of relative traffic models are used to generate the results for observation: Uniform traffic, Poisson traffic with mean one, and Poisson traffic with mean ten. The Uniform traffic case is examined first. To summarize, the less uncertainty regarding the destination, the lower the entropy. Therefore, the Uniform traffic case is expected to perform worse than the Poisson traffic case with mean one, while it is expected to have similar performance to the case with Poisson traffic with mean ten.

Suppose the elements of the relative traffic matrix are all uniform on the main diagonal, which is always zero because a node may not send packets to itself. Therefore the minimum rate that routing bits of information are generated is given by:

$$B = K(N-1)^2 \log_2(N-1). \tag{3.44}$$

Suppose N nodes are randomly scattered in a grid and consider path loss, multipath fading, and shadow fading between each pair of nodes. If for each node there are exactly P output links having link capacity C_{common}, which is substantially greater than zero and $N-1-C_{common}$ output links, each with capacity equal to zero. Then, the switching capacity of each node will be maximized if each of its P output links with non-zero capacity and with probability of $\frac{1}{P}$, the maximum rate that switching decisions can be made by node i is given by:

$$R_i = \frac{C_{common}}{M} \frac{1}{P} \log_2 \left(\frac{1}{P} \right). \tag{3.45}$$

Summing all nodes in the network and comparing the switching capacity of the network against the exogenous demand,

$$K \leq \frac{N}{(N-1)^2 \log_2(N-1)} \frac{C_{common}}{M} \frac{1}{P} \log_2 \left(\frac{1}{P} \right). \tag{3.46}$$

Combining equation 3.46 equation 3.41, the equation for the capacity of the network with respect to the relative traffic matrix in bits per second per hertz, the result

shows that under Uniform traffic conditions, the network capacity is bounded by:

$$C \leq \frac{NC_{common}}{\log_2(N-1)} \left[\frac{1}{P} \log_2 \left(\frac{1}{P} \right) \right] \tag{3.47}$$

and for large N,

$$C \leq \frac{NC_{common}}{\log_2 N} \left[\frac{1}{P} \log_2 \left(\frac{1}{P} \right) \right]. \tag{3.48}$$

For a large network, the network capacity scales as Moore Bound, or $\frac{N}{\log_2 N}$. The theorem states that for a network with fixed connectivity, each node of the network brings a fixed capacity and the average number of hops scales as $\log_2(N)$. Therefore, each packet consumes network resources on an average of number of $\log_2(N)$ links and thus the overall network capacity must scale as Moore Bound.

Figure 3.2 shows the network capacity in bits per second per hertz for a 9-node network without shadow fading. Similarly, Figure 3.3 presents the results for a 25-node network without shadow fading. The trend follows that as more nodes are added to the network, the better the overall network capacity.

3.5.2 Simulation for Poisson Traffic

The first set of experiments with uniform traffic matrix as the baseline was shown in Figure 3.2 in the previous section. The relative traffic matrix varies such that Figure 3.4 has Poisson distributed traffic with mean one, and Figure 3.5 has Poisson distributed traffic with mean 10. Figure 3.6 shows the effect shadow fading has on the overall network capacity for a 9-node network with Poisson traffic mean one. Each traffic matrix is as described with the main diagonal equal to zero indicating that no node may send packets to itself. Each plot includes the average, minimum, and maximum of the overall network capacity from ten simulations. The average is derived from ten runs. The spread between the worst, average, and best cases is small and the spread rapidly decreases as the number of nodes in the network increases. The more nodes are used within a service region, the less the spread becomes and all ten trials approach the average result.

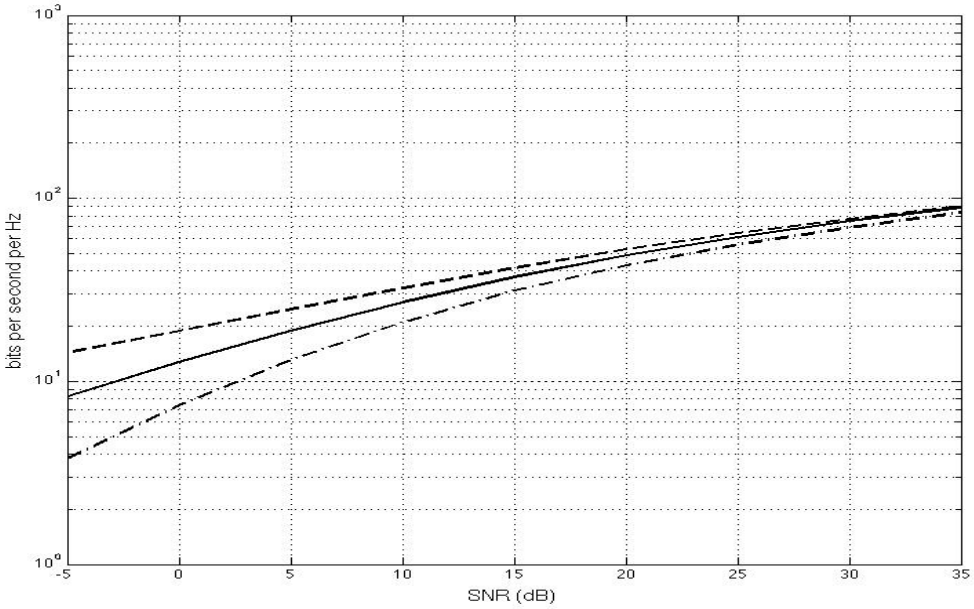

Figure 3.2: 9-node network with relative traffic elements of ones with path loss and multi-path fading (maximum, averaged of 10 trials, and minimum).

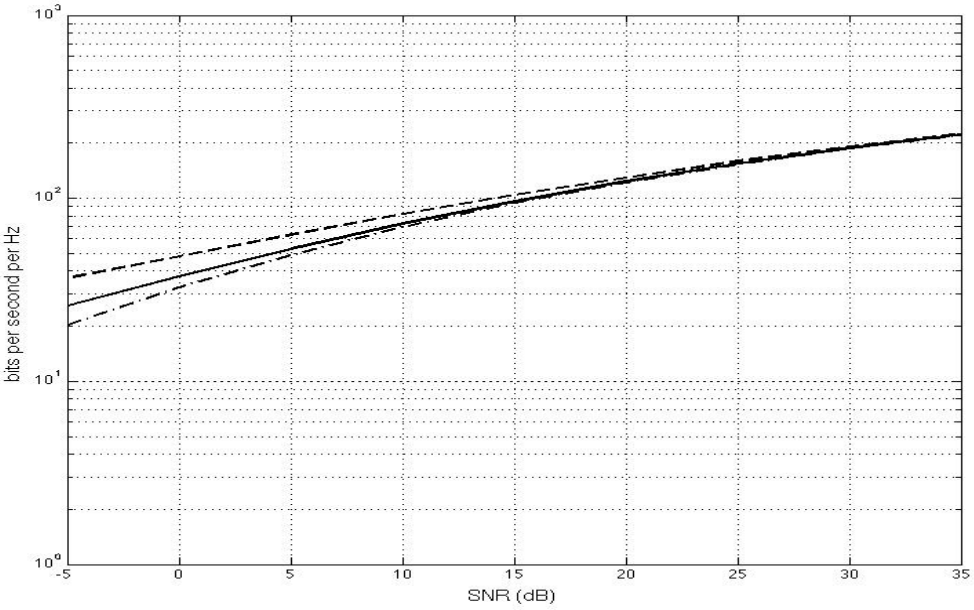

Figure 3.3: 25-node network with relative traffic elements of ones with path loss and multi-path fading (maximum, averaged of 10 trials, and minimum).

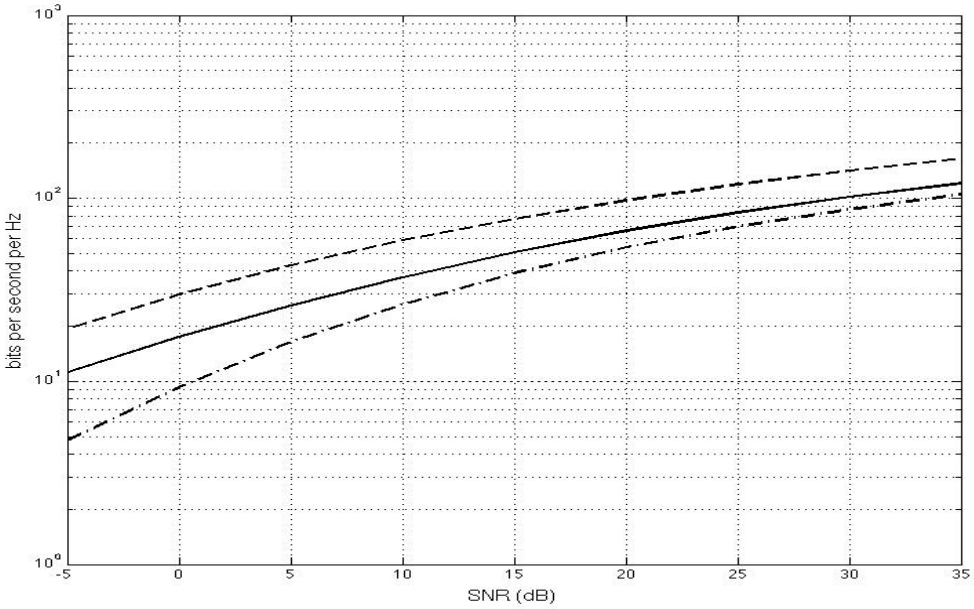

Figure 3.4: 9-node network with relative traffic elements Poisson distributed with mean one with path loss and multi-path fading (maximum, averaged of 10 trials, and minimum).

Not surprisingly, the upper bound on the overall network capacity increases with increasing SNR. The traffic elements also play a small role in the capacity bound. Relatively speaking, Poisson traffic with mean 10 has a smaller variability than the Poisson traffic with mean 1. The uncertainty is greatest when all destinations are equally likely, while greater variability translates to lower destination uncertainty, or lower entropy. Lower entropy results in less bits to transfer the same amount of information, thus resulting in greater overall network capacity.

Shadow fading is included in Figure 3.6. Shadow fading is often analyzed as a serious impairment for conventional infrastructure networks, however, the results here suggest that shadow fading is less concerning for a peer-to-peer network. Under severe shadow fading, the link between the pair of nodes is simply not used and an alternative path is used instead. Our results show the shadow fading in the simulation has a slightly beneficial effect on the overall network capacity. This might be because our path loss model assumes the received power is averaged over shadow fading and multi-path fading.

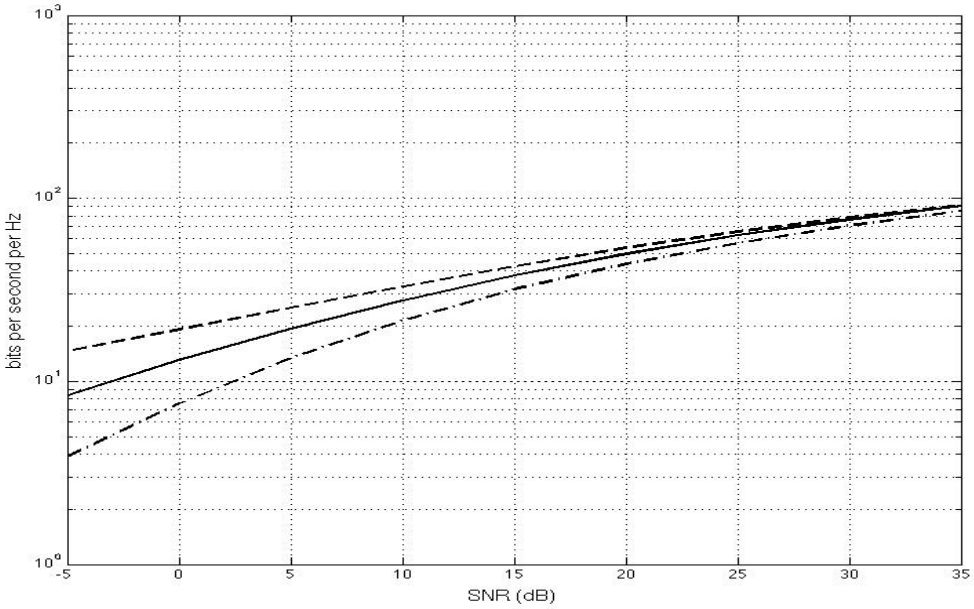

Figure 3.5: 9-node network with Poisson distributed relative traffic elements with mean ten, including path loss and multi-path fading (maximum, averaged of 10 trials, and minimum).

When shadowing is considered and less than the predicted path loss model, these paths may result in an increase in the capacity matrix elements and thus improves the overall capacity bound.

For the second set of results (Figures 3.7, 3.8, and 3.9), a 25-node network is simulated to show the improvement on the overall upper bound when additional nodes are used in a service region. A total of ten simulations were run for each case; the average, minimum, and maximum are plotted. Figure 3.3 shows the case where the traffic matrix is of unity without shadow fading. Figure 3.7 shows the scenario where the traffic matrix is Poisson distributed with mean one, and Figure 3.8 shows the scenario where the traffic matrix is Poisson distributed with mean 10. All matrices' main diagonals are defaulted to zero. For both the Poisson distributed traffic, the matrices are not necessarily symmetrical as described earlier. Finally, Figure 3.9 shows the scenario where traffic elements are Poisson distributed and includes the shadow fading to the propagation model.

It is worthwhile to note that the 25-node network provides greater overall ca-

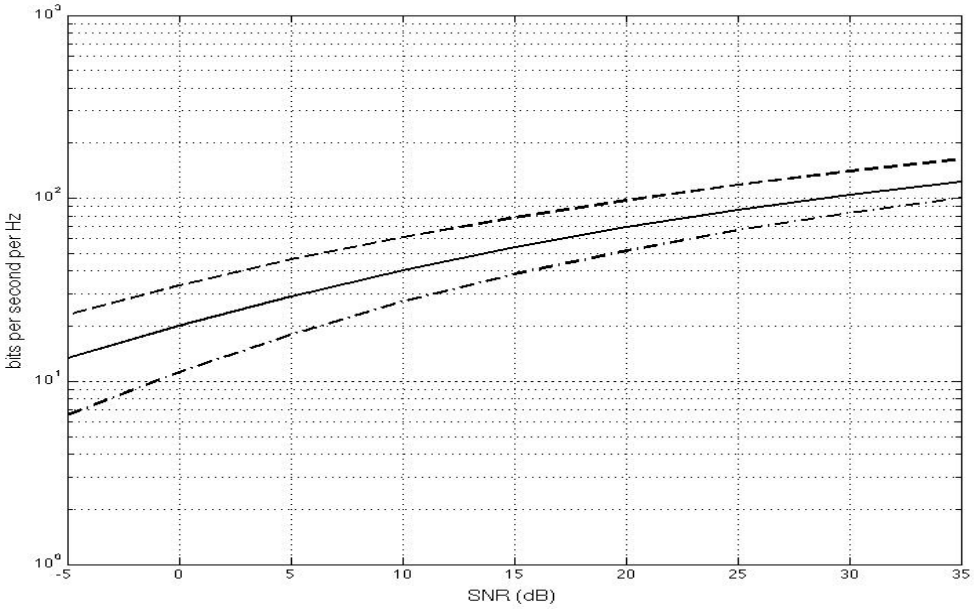

Figure 3.6: 9-node network with relative traffic elements Poisson distributed with mean one with path loss, multi-path fading and shadow fading (maximum, averaged of 10 trials, and minimum).

pacity, but the overall trend doesn't change. The network with Poisson traffic of mean one is still better performing than with mean ten or uniform traffic. Shadow fading still has a small beneficial effect on the capacity bound. Such results are consistent with the 9-node, 64-node, and 100-node cases.

It is not surprising that the upper bound on overall network capacity increases with increasing SNR. The increase is approximately logarithmic with SNR, as in accordance with Shannon theory. However, for smaller values of SNR, the rate of increase of capacity with SNR is faster than logarithmic. This is because as SNR increases, more links from each node become usable and the switching capacity of nodes increase accordingly, which is in addition to the logarithmically increasing capacity of each link.

For a fixed SNR as N increases, the capacity bound scales approximately with Moore bound. This result also agrees with Gupta and Kumar's per node capacity analysis [19]. The normalized SNR remains the same as additional nodes are added but the service region still increases. Since the number of nearby nodes remains relatively fixed, the

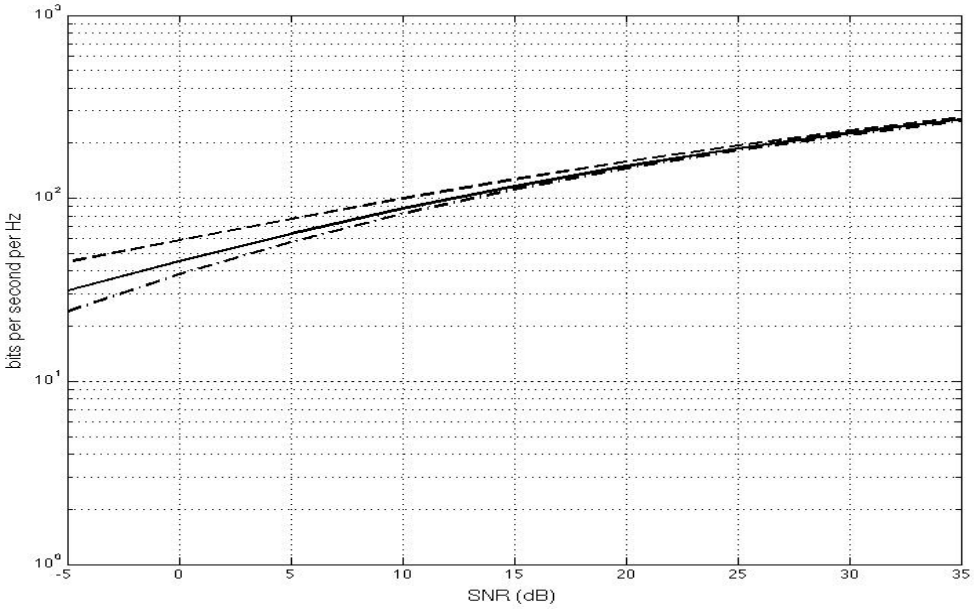

Figure 3.7: 25-node network with relative traffic elements Poisson distributed with mean one with path loss and multi-path fading (maximum, averaged of 10 trials, and minimum).

most significant links are likely to be the closest neighbors, thus the switching capacity of each node is relatively unaffected by the addition of more nodes. As N increases, the switching entropy of each node scales approximately logarithmically with N. Therefore each additional node will bring additional network switching capacity. The average number of hops needed to route traffic scales approximately logarithmically with N.

Figure 3.10 shows the overall result for capacity versus the number of nodes that reside in a network, with traffic elements of Poisson distribution with mean 10 and with shadow fading. Similar result for a different propagation model is presented in [5].

3.5.3 Highly Non-Uniform Traffic

The case of highly non-uniform traffic where only a few nodes (root nodes) generate exogenous traffic and exogenous traffic generated by other nodes are destined for only these root nodes is also considered. This traffic model could apply to popular radio mesh networks where a few access nodes are attached to the infrastructure. Therefore,

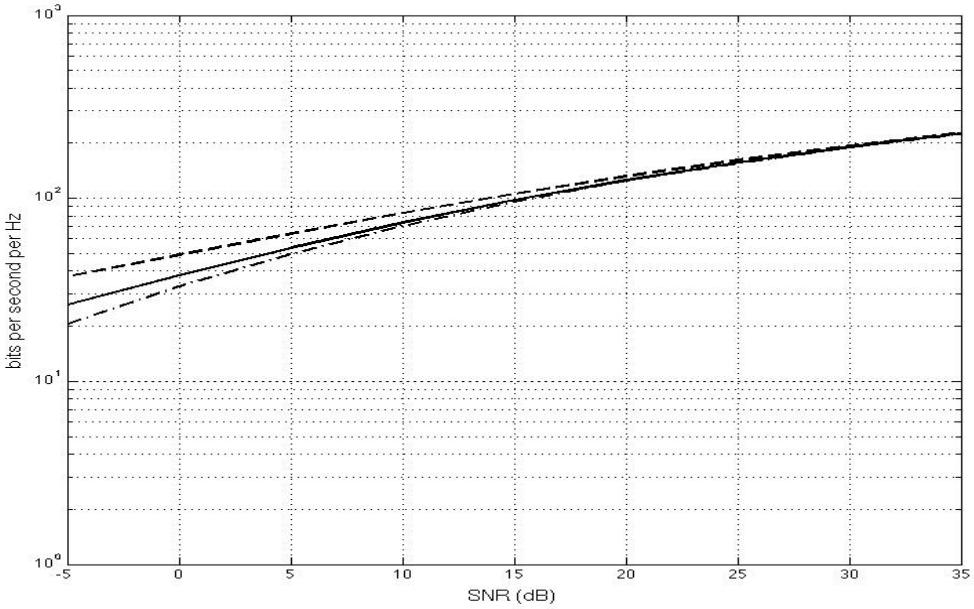

Figure 3.8: 25-node network with Poisson distributed relative traffic elements with mean 10, including path loss and multi-path fading (maximum, averaged of 10 trials, and minimum).

traffic from the infrastructure must pass through one of the root nodes to route to other nodes. Similarly, traffic intended for the infrastructure must pass through one of these root nodes. Rearrange the traffic matrix so that non root nodes are labeled R+1, R+2, and root nodes are labeled by indices 1, 2, ..., R:

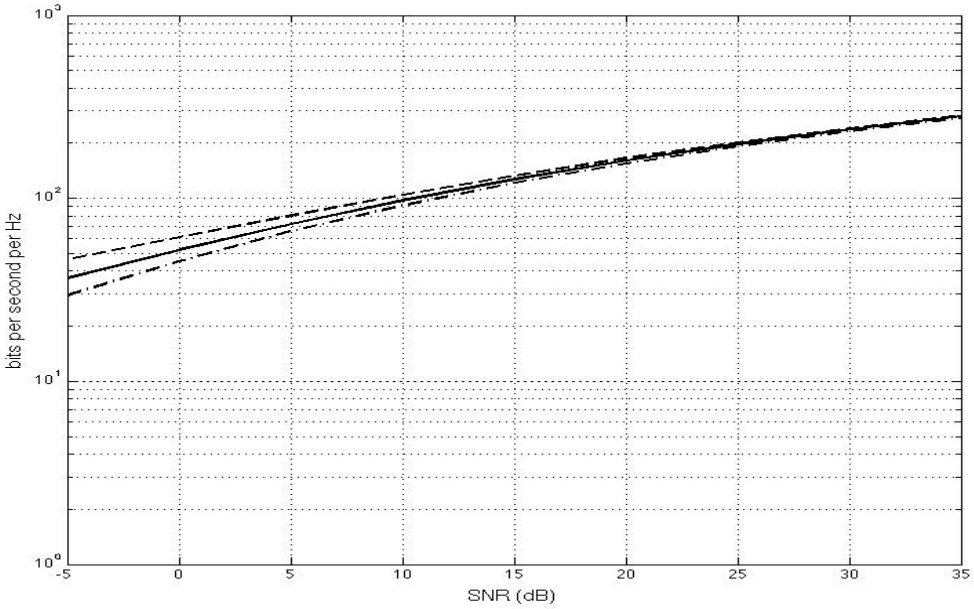

Figure 3.9: 25-node network with relative traffic elements Poisson distributed with mean one with path loss, multi-path fading, and shadow fading (maximum, averaged of 10 trials, and minimum).

$$T = \begin{bmatrix} 0 & t_{1,2} & t_{1,3} & \therefore & t_{1,R} & t_{1,R+1} & t_{1,R+2} & \dots & t_{1,N} \\ t_{2,1} & 0 & t_{2,3} & & t_{2,R} & t_{2,R+1} & t_{2,R+2} & & t_{2,N} \\ t_{3,1} & t_{3,2} & 0 & & t_{3,R} & t_{3,R+1} & t_{3,R+2} & & t_{3,N} \\ \vdots & & & \ddots & & & & & \vdots \\ t_{R,1} & t_{R,2} & t_{R,3} & \dots & 0 & t_{R,R+1} & t_{R,R+2} & \dots & t_{R,N} \\ t_{R+1,1} & t_{R+1,2} & t_{R+1,3} & & t_{R+1,R} & 0 & 0 & & 0 \\ t_{R+2,1} & t_{R+2,2} & t_{R+2,3} & & t_{R+2,R} & 0 & 0 & & \\ \vdots & & & & \vdots & \vdots & & \ddots & \vdots \\ t_{N,1} & t_{N,2} & t_{N,3} & \dots & t_{N,R} & 0 & 0 & \dots & 0 \end{bmatrix}. \quad (3.49)$$

For this highly non-uniform traffic matrix, consider two cases:

1. The number of root nodes R set at 3

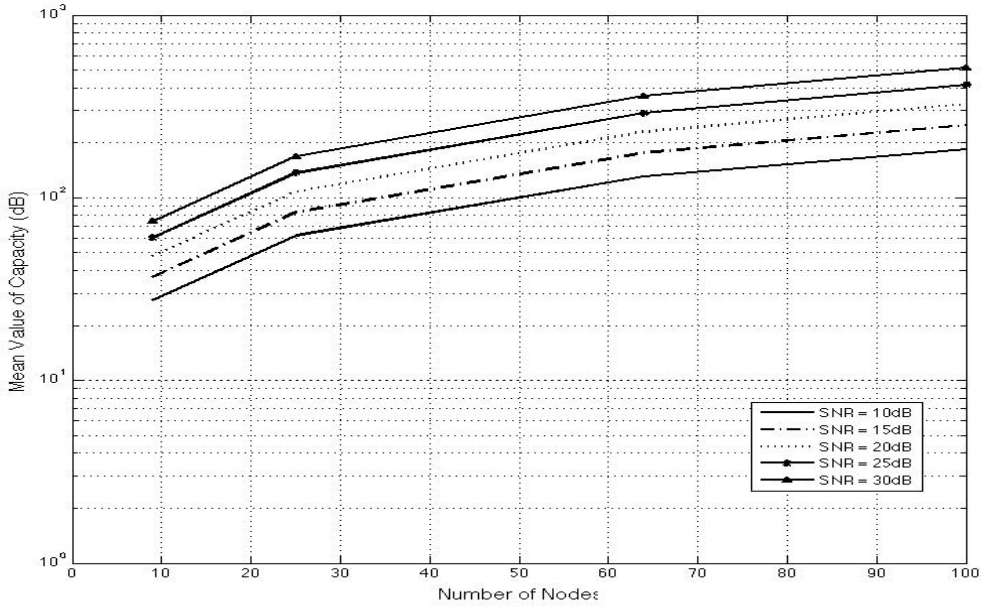

Figure 3.10: Capacity versus number of nodes in the network for traffic element of Poisson distribution with mean 10 with shadow fading.

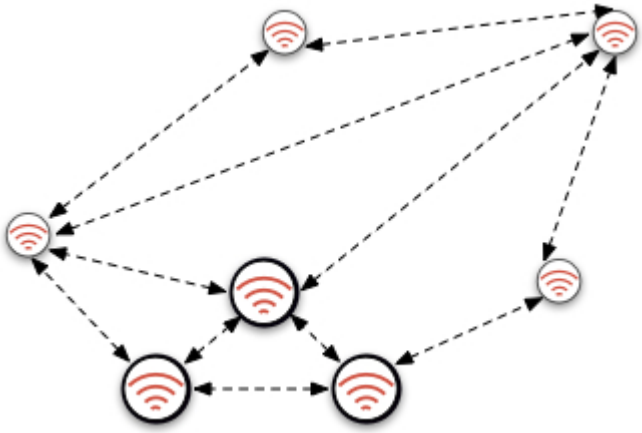

Figure 3.11: Sample configuration of three root nodes (bigger nodes) being the access points for the infrastructure, the regular wireless nodes are shown as the smaller nodes

2. The number of root nodes R set at 5

Figure 3.11 shows a possible configuration of three root nodes attached to the infrastructure, where the bigger nodes represent the root nodes and the smaller wireless nodes represent standard ad hoc nodes. For the case with a highly non-uniform traffic

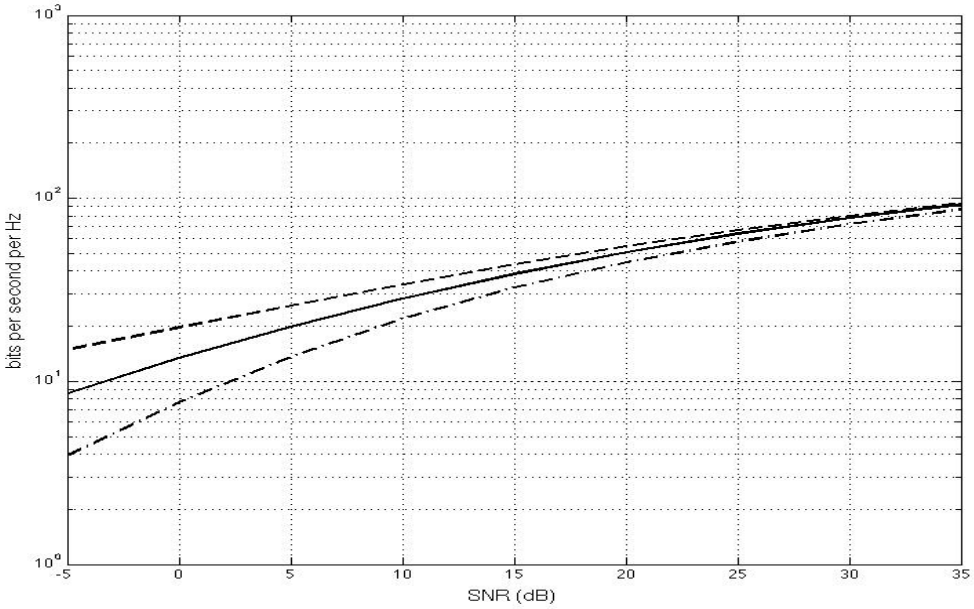

Figure 3.12: 9-node network with three nodes as root nodes, without shadow fading (maximum, averaged of 10 trials, and minimum).

matrix where there are only three nodes generating exogenous traffic and exogenous traffic generated by other nodes are destined for only these three nodes, simulations show that all cases are visually indistinguishable. However, there is a slight increase of capacity for the network using root nodes in the 9-node network case, and indistinguishable for networks with a higher number of nodes. Figure 3.12 shows the case of a 9-node network with three root nodes and Figure 3.13 shows the comparison between a 9-node network with unity traffic matrix versus the case with three root nodes. The case with root nodes is represented dotted-dashed line and the black solid line is the network without root nodes. Figure 3.14 shows the parallel result of figure 3.13, but with 25 nodes in the network. It is easy to see that for the case with a 25-node network, the results are visually indistinguishable.

The three root nodes are picked based on their locations in the service area. The three nodes closest to the origin (0,0) are picked. For the five root nodes case, they are picked using the same method. Figure 3.15 shows the case with 5 root nodes, the

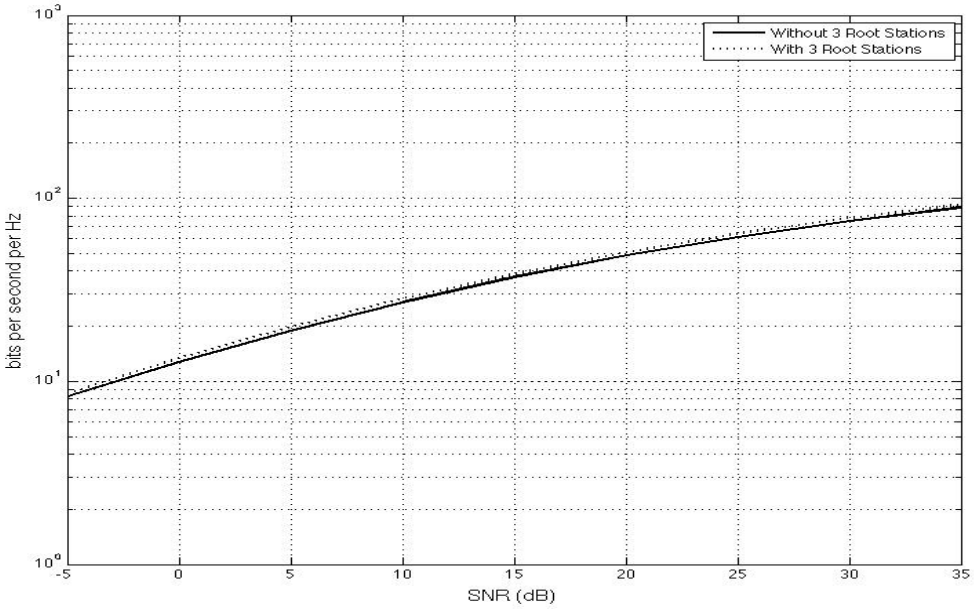

Figure 3.13: 9-node network with three nodes as root nodes, without shadow fading, compare to the 9-node network with unity traffic.

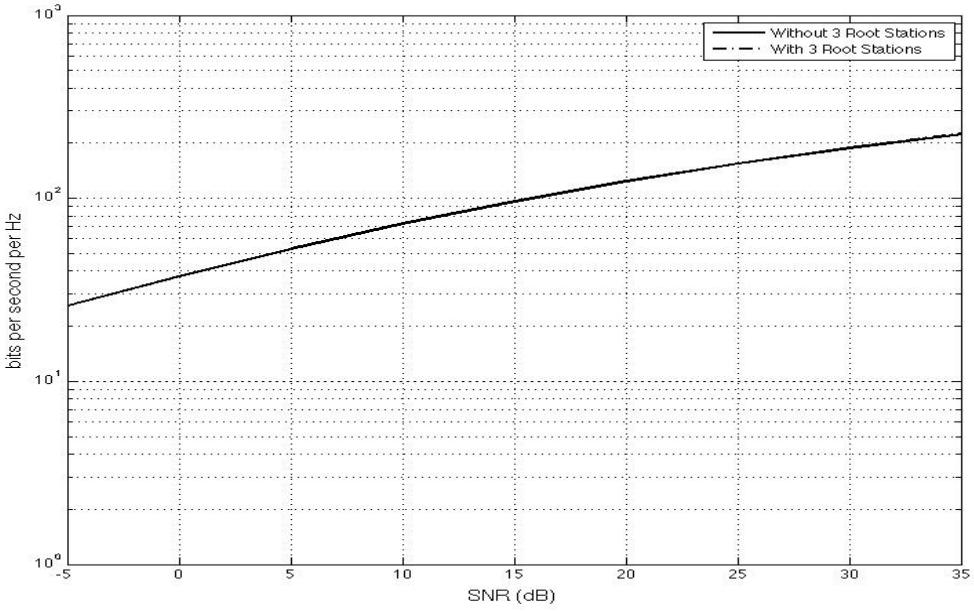

Figure 3.14: 25-node network with three nodes as root nodes, without shadow fading.

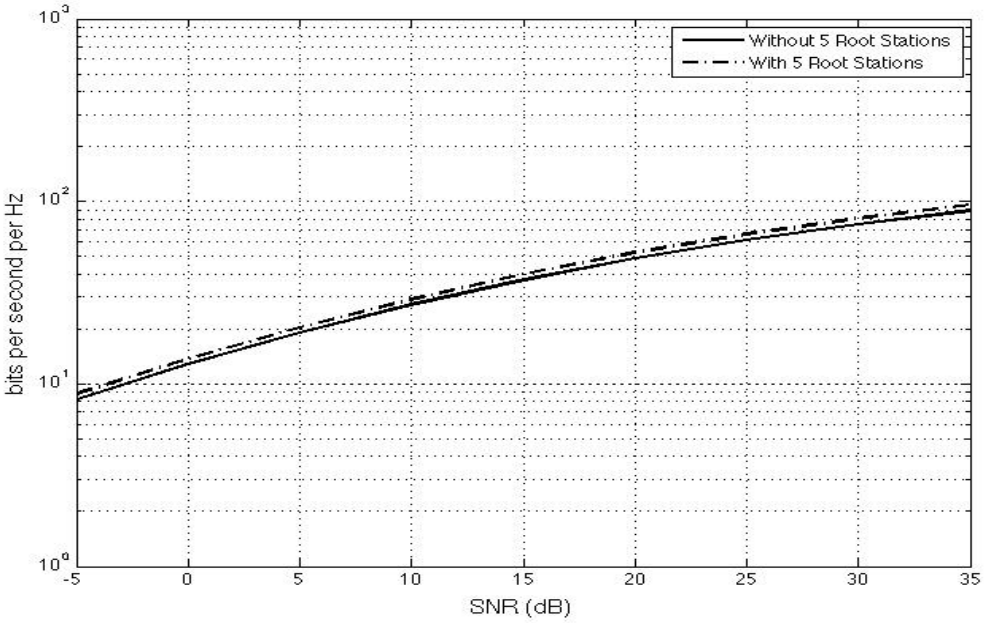

Figure 3.15: 9-node network with five nodes as root nodes, without shadow fading.

differences are slightly more visible than the 3 root nodes case.

Since the number of switching decisions per unit time for each node is independent of the traffic matrix, the bound must increase with N and therefore should be higher than the peer-to-peer case since the entropy is smaller. However, for the highly non-uniform traffic case, the increase in network capacity with increasing N is an artifact of the bounding technique employed. This is because although each additional node brings new switching resources, the network is restricted by the bottleneck where all traffic must flow through the root nodes. Therefore, the corresponding network capacity should be independent of the total number of nodes.

3.6 Conclusions

In this chapter, information theory was applied to switching network. The minimum amount of information necessary to specify the destination a message is intended for was determined and compared against the maximum rate at which a wireless node

can switch information packets. This enabled an upper bound of the overall capacity of a network of N peer-to-peer wireless nodes to be determined. The model used to simulate this bound included propagation impairments, SNR constraints, and an additional constraint that a given node can either send or receive. This is a pure upper bound because interference is ignored. No other peer-to-peer routing algorithm can possibly produce a greater bound than this.

As expected for a large SNR, the upper bound on overall capacity increases approximately logarithmically with SNR. It also increases as $\frac{N}{\log_2 N}$. As more nodes are added, the greater switching resources become available and the average number of hops increases. Any randomly chosen distribution has approximately the same performance as averaged over many distributions. Also, because of the greater degree of routing diversity, the effects of shadow fading are quite small compared to its effects on infrastructure networks.

Although this bound is not achievable in the real world, this upper bound is useful for several reasons. First, it provides a yardstick against future work for networks with node cooperation because this bound can be used as a metric against any potential improvement that may be achieved by different cooperative techniques. Second, this bound may also be compared against other novel media access protocols and routing strategies. Finally, this bound also provide insights to the constraints imposed by highly non-uniform traffic matrices as provided by the popular wireless mesh networks over metropolitan service areas.

Chapter 3, in part, has been submitted for publication as appeared in the following paper: Anthony S. Acampora and Louisa P.S. Ip, "Information Theoretic Bounds on the Capacity of Peer-to-Peer Wireless Networks with Hop-by-Hop Routing," IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC 2007) and Anthony S. Acampora, Michael Tan, and Louisa P.S. Ip, "Fundamental Bound on the Capacity of Ad Hoc Networks with Conventional Hop-by-Hop Routing," Wireless Communications 2007 CNIT Thyrrenian Symposium, pages 127-133,2007. The dissertation author was the primary investigator and co-author of this paper.

Chapter 4

Lower Bound of Ad Hoc Wireless Network With Node Cooperation Using Time-Share Scheme

4.1 Introduction

Last chapter presented the information theoretic bound on the capacity of a peer-to-peer wireless ad hoc network with hop-by-hop routing. The bound derived earlier used information theory, which was applied to a switching network. The maximum rate that switching decisions can be made by the network was compared to the rate that decisions must be made. This upper bound does not require that the optimized connectivity and flow be found, but by applying an easily computable constraint on the maximum rate at which switching decisions can be made by network nodes for any connectivity and flow to determine the highest possible throughput for a specific relative traffic matrix. It is the best theoretical bound in that the physical world can hope to achieve. While the bound is not achievable, it is a good yardstick to measure the cooperation scheme studied in this chapter.

In this chapter, the lower bound of node cooperation is studied. Node cooperation has attracted numerous researchers as wireless peer-to-peer ad hoc network did. Sendonaris showed in his short paper that user cooperation can lead to a higher data rate, reduced power for users, and reduced sensitivity to channel variations [45]. With wireless ad hoc networks, energy consumption is of utmost important because nodes are usually operated by batteries and have limited power capacity. With this in mind, one may take advantage of spatial diversity with no extra transmission cost to the transmitting node due to the nature of broadcasting. A reward system may be implemented to motivate nodes within hearing distance to assist in relaying the packet. Researchers in [31] considered the case where packets from a source node are sent to a destination node using cooperating wireless relays to minimize total energy consumption. Cooperation is also a method of increasing network robustness because different paths usually encounter different fading. Thus cooperative transmission is an efficient way to combat multipath and shadowing fading. Some researchers placed their focus on scalability, security, routing algorithms, energy efficiency, and network capacity. Meanwhile, researchers such as Gonzales-Velazquez et al. studied synchronization using groups of oscillators within the

same hop depth become phase synchronized with the adjacent hop depths. Such that when a group of nodes within the same hop depth finished sending, they listen to nodes from one hop depth nearer the data collector to maintain synchronization [17]. Others remain with the more traditional TDMA method to ensure synchronized transmission. While a majority of researchers studied node cooperation up to a pair of nodes as with Sendonaris et al. [43, 44] which relies on orthogonal subspace, Laneman et al. [27], whose group also uses an orthogonal subspace scheme to explore spatial diversity, and Yazdi et al. which uses a nonorthogonal transmission scheme based on time slots (frames) [57]. All three independently performed research mentioned previously placed their focus on no more than two transmitters or two receivers cooperating together. Rarely researchers studied beyond two nodes cooperatively transmit and/or receive together. Scaglione et al. [41] considered the case with multiple nodes cooperatively transmitting to the destination node, but capacity bound was not their research focus. It is not surprising however, because of the added complexity of involving more nodes to cooperatively act together in a mobile environment.

This chapter presents the effects on the capacity of a network when multiple nodes are cooperatively transmitting packets. To simplify the problem, this chapter only considers the case where the transmitters may cooperatively transmit information to a single receiver only, even though cooperation with both transmitter and receiver provide significant capacity gain over transmitter only or receiver only cooperation [21, 32]. Packets are assumed to be either arriving at the receiving node group at the same time or some synchronization scheme is implicit and employed. To further simplify the problem, the work presented in this chapter attempts node cooperation without frequency reuse, that is, only one node may transmit or receive in a given time slot, commonly known as the time-share bound. This scheme is simple in that no attempt is done to optimally utilize all resources available for transmission by means of interference avoidance or by other schemes. These time-share results are compared to the previous theoretic upper bound on the capacity of an ad hoc network without cooperation. The purpose of this study is to determine if there are any benefits in allowing nodes to cooperate and if

so, how much improvement is gained by allowing more nodes to cooperatively transmit packets. There have been numerous of studies conducted on paired nodes cooperation but very few emphasis on any higher number of nodes cooperating together. Here, two or more nodes are allowed to cooperate together that will give the best network throughput for a defined specific network mode. The main contribution of this chapter is to determine how much improvement can a network gain by allowing more than two nodes to cooperate and if it is reasonable to forgo more nodes to cooperate.

The lower bound analysis starts with using the relative traffic matrix and point-to-point Shannon capacity matrix as described earlier. The same two matrices to determine the lower bound capacity with cooperation and more matrices are created as necessary for higher order of node cooperation. Each node transmits with P watts and the location of the nodes for each of the ten trials are identical to the ten trials used in the simulation for the information theoretic upper bound. The results showed that two-node cooperation improved the overall capacity significantly from peer-by-peer routing without frequency reuse. Three-node or more in cooperation does not provide significant improvement over the two-node cooperation. However, depending on the transmission frequency used, the small gain could be useful in some applications. Not surprisingly, the results also showed that without frequency reuse, this naive scheme could not outperform the information-theoretical upper bound with frequency reuse.

4.2 Capacity Matrix and the Relative Traffic Matrix for the Node Cooperation Case

The network of interest is composed of N nodes where each node may send or receive packets to or from another single node, paired nodes, and three or more nodes up to $N-2$ nodes. For convenience, the cooperative grouping of nodes is defined as "phantom node". The concept is to group the cooperating nodes as a black box, or appear as a single node to the outsiders, with different rules in calculating the capacity link. The same constraints exist; each node may only send or receive at a given time

and no nodes may send and receive simultaneously. Furthermore, when a source node is sending packets to a receiving node via another single node, it behaves as a peer-to-peer network as in the previous upper bound.

To simulate this network model, the link capacity matrix and the relative traffic matrix are used. Use Shannon Theory to calculate each element of the capacity matrix under the interference-free environment:

$$C = W \log_2(1 + \rho), \tag{4.1}$$

where W is set to one in order to present the results in per hertz and

$$\rho = \frac{P}{NW}, \tag{4.2}$$

where N is the noise from the channel and W is the available bandwidth, set to unity in the absence of interference. The propagation model includes impairments such as path loss, multi-path fading, and shadow fading between each node as defined under chapter 2. Thus, incorporating path loss, multi-path fading with random variable X, and lognormal shadow fading, the SNR between each nodes is adjusted,

$$\rho_{i,j} = \rho \left(\frac{d}{R} \right)^4 e^X 10^{\frac{\epsilon}{10}}, \tag{4.3}$$

where ρ is the SNR in linear scale and ϵ is Gaussian distributed, zero mean with standard deviation of 6 dB. $\rho_{i,j}$ is the SNR from node i to node j. Using this SNR with impairments to fill in the capacity matrix with normalized bandwidth using Shannon capacity from equation 4.1,

$$C = \log_2(1 + \rho_{i,j}). \tag{4.4}$$

This new capacity must be calculated when a node is sending to a phantom node. In this case, to find the worse case, take the smaller of the capacity elements. The capacity link from node i to nodes $\{j, k, l\}$ is defined as:

$$C_i^{j,k,l} = min\{C_{i,j}, C_{i,k}, C_{i,l}\}. \tag{4.5}$$

There is a separate capacity matrix used for storing the capacity links when a phantom node send packets to a single node and when a single node transmit to a phantom node. The predetermined capacity table is similar to the idea of table-driven routing protocols used to maintain up-to-date routing information between nodes within a network [39]. For each number of nodes cooperating together, a new capacity matrix is generated while the traffic matrix expands to record the new traffic load on the phantom nodes. For example, for a 4-node network with paired node cooperation, in addition to the original capacity matrix for peer-to-peer links, there will also be a second capacity matrix where the phantom node pairs are indicated by "$< n_1, n_2 >$":

$$C = \begin{bmatrix} 0 & C_{1,2} & C_{1,3} & C_{1,4} \\ C_{2,1} & 0 & C_{2,3} & C_{2,4} \\ C_{3,1} & C_{3,2} & 0 & C_{3,4} \\ C_{4,1} & C_{4,2} & C_{4,3} & 0 \\ C_{<2,3>,1} & 0 & 0 & C_{<2,3>,4} \\ C_{<2,4>,1} & 0 & C_{<2,4>,3} & 0 \\ C_{<3,4>,1} & C_{<3,4>,2} & 0 & 0 \\ 0 & C_{<1,3>,2} & 0 & C_{<1,3>,4} \\ 0 & C_{<1,4>,2} & C_{<1,4>,3} & 0 \\ 0 & 0 & C_{<1,2>,3} & C_{<1,2>,4} \end{bmatrix}, C_{i,j} = 0, \forall i = j. \tag{4.6}$$

For the cooperation case, node "i" for equation 4.6 can be representing two or more nodes. Because the capacity link is identical for node i to node j and vice versa, one capacity matrix is sufficient to represent the direction of paired node to single node and from the single node to paired node. A separate matrix is required for three-node group, four-node group, and so on.

This dissertation assumes perfect timing and synchronization when node cooperation is used. However this is hardly the case in the real world. There are many ways to combat synchronization with media access protocols. Vakil et al. [53] uses a threshold, or relay zone, to select the closest neighbor within a certain capacity region for node cooperation. This method has been experimented and simulated under this model, but the results were not significant. Although it did create a slight degradation in the overall network throughput, it was not used because perfect time synchronization is assumed for comparison. Others use time slots which nodes have a certain amount of time to accept or transmit packet before the next hop. Such routing algorithms are not efficient because dead time is wasted in a slot. There are other models that assumed perfect synchronization and full channel state information, such as the work presented by Stanković et al. in [47]. Even though the model here assumes perfect time synchronization, it is also important to examine how imperfection of time synchronization would effect the signal quality, time delay, and network throughput. It is a complex topic in estimating the receiver's tolerance to imperfect time synchronization. However, this topic of performance tolerance to non coherent scenario is beyond the scope of this dissertation.

In the case where phantom nodes are used to cooperatively send packets to a single node, the capacity link is based on the sending nodes' SNR. For two nodes sending with P watts, or square root of P in volts, add the two voltages together and take the square of the resulting voltage to obtain watts. Using super position, it is simple to convert the transmitting power to a unit of voltage and add linearly. For example, if node j and node k would like to send a packet cooperatively to node i,

$$v_{jk}^{i} = v_{j,i} + v_{k,i} = \sqrt{P_{j,i}} + \sqrt{P_{k,i}}. \tag{4.7}$$

Taking the square on both sides to obtain power in watts, we have

$$P_{j,k}^{i} = (v_{j,k}^{i})^2 = \left(\sqrt{P_{j,i}} + \sqrt{P_{k,i}}\right)^2. \tag{4.8}$$

Similarly, this scheme can be extended for the three or more nodes case:

$$P^i_{j,k,l} = (v^i_{j,k,l})^2 = \left(\sqrt{P_{j,i}} + \sqrt{P_{k,i}} + \sqrt{P_{l,i}}\right)^2. \tag{4.9}$$

Finally, use the same relative traffic matrix as defined by the upper bound in equation 2.7 to represent the exogenous traffic generated due to information delivered from node i to node j. The diagonal elements of the relative traffic matrix are zeros because a node can not send packets to itself. However, unlike the capacity matrix, the relative traffic matrix need not be symmetric because the source and destination nodes could be of different equipment. The traffic matrix will expand as node pairs or groups are being used. For example, the traffic matrix starts out as an N by N matrix, when traffic is being routed to a phantom node, the new traffic at the phantom node to the intended source node is added to the traffic matrix (i.e $N + 1$ by N). The traffic from the phantom node to the destination node is treated the same as the traffic from a peer to another peer. Each time a traffic element has successfully reach its destination, the traffic element is removed from the traffic matrix. The process continues until the sum of the traffic matrix is zero, or when all traffic has been flowed.

4.3 Routing Algorithm

For this lower bound without frequency reuse, only one node or a phantom node may send if and only if the network is free at any given time. This is commonly known as the time-share bound. Traffic is allowed to flow as long as the flow follows these two constraints; a single node may transmit a packet to a phantom node or to another single node, but a phantom node may only send to a single node and not to another phantom node. By placing the second restriction, this bound allows only transmitter cooperation and not receiver cooperation. Figure 4.1 is a sample of how traffic may flow to and use a phantom node as a relay node.

Traffic may also flow to more intermediate hops as in Figure 4.1(d), an extension of (b), to an extra relay node before transmitting to the destination node. This is known as a three-hop route and may only be selected if this three-hop route outperform the

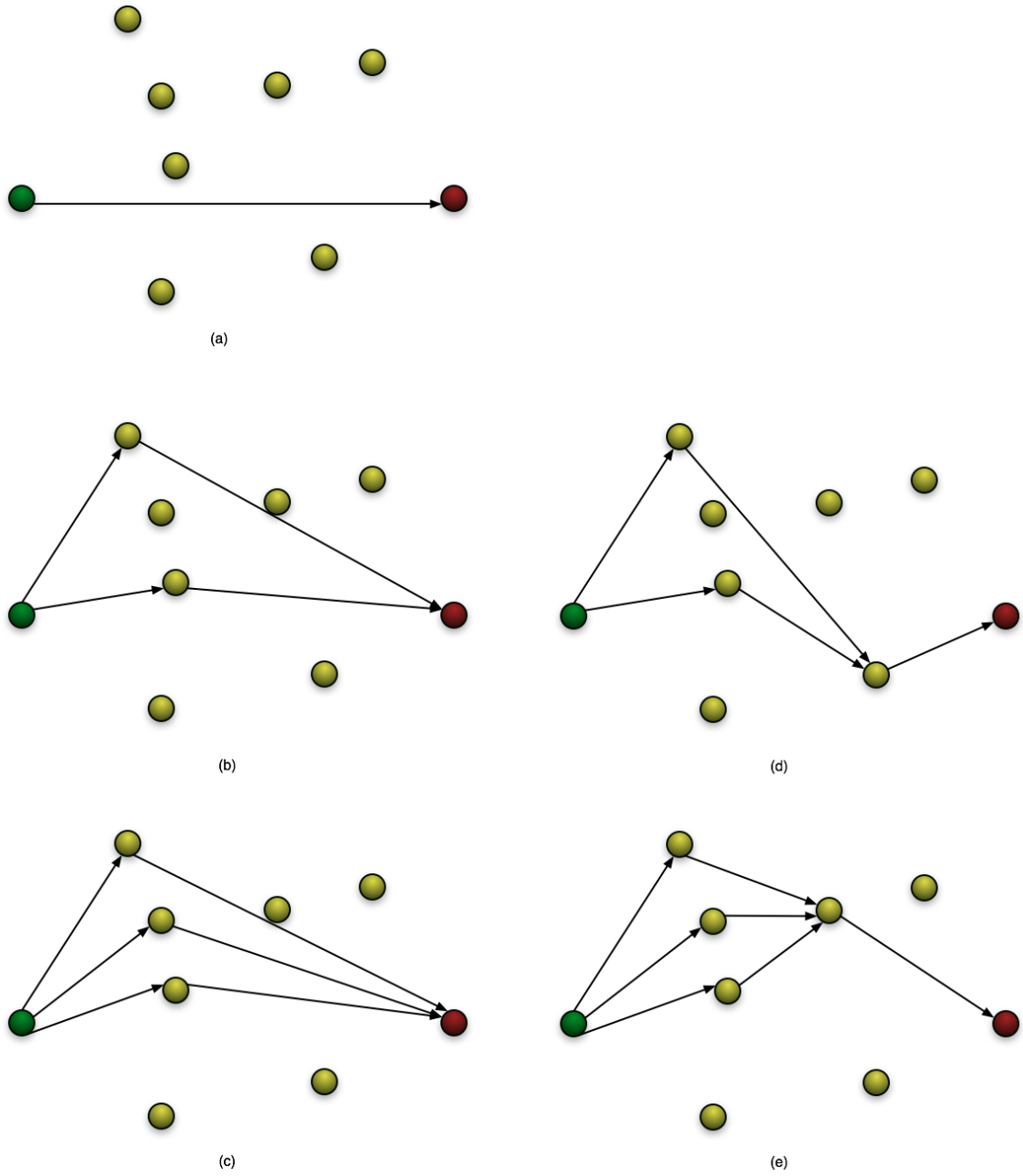

Figure 4.1: Sample traffic flow with only one or two hops considered, (a) direct hop, (b) relay via a paired node, (c) relay via three node group, (d) three-hop relay via a paired node and (e) three-hop relay via three-node group.

two-hop path in terms of time required for transmission. Thus, a source node may use as many hops as necessary, the only constraint being that each additional hop must improve the network capacity. Therefore, a four-hop path must take less time to transmit than a

three-hop path. This calculation is purely idealistic, as no overhead is being considered. In reality, multi-hop would require each relay node to use its limited power to receive and transmit the packets as well as the overhead necessary to route the packets to the correct destination.

An iterative and exhaustive method is used to finds the best optimal pairing of nodes and the amount of hops that would provide the best capacity achievable. The best capacity link is used for routing, but when dealing with phantom nodes, the worse capacity link of the cooperating nodes should be selected to simulate the lower bound. To determine the number of hops necessary, first consider the case in finding the optimal peer-to-peer path. Each node in the network find the best relay path to its intended destination, the time required for the direct path from source to destination node is calculated first. The simulation then extends the search with an extra hop. For the peer-to-peer case, no phantom nodes are considered. If the total time required to send the packets from the source node to the destination node is smaller for the two-hop path than the direct hop, keep the two-hop path. Repeat this simple iterative process for three-hop, four-hop, and so on until adding an extra hop would not improve the capacity. The iteration stops here because the minimum time path has been discovered. This exhaustive search determines the absolute minimum time the network can achieve with the given constraints.

Apply the same exhaustive search method and criteria of minimum time constraint in searching for the best path with the minimum number of hops to determine the optimal number of nodes for cooperation. Repeat the procedure for phantom nodes composed of two nodes paired together first and record the result. Then, repeat the procedure for three-node group, four-node group, and up to six-node group for the simulation. A node will only transmit the packet to a higher number of grouped nodes if and only if a hop takes the least amount of time for transmission. For example, for the simulation with phantom nodes consisting of three nodes, a combination of four nodes took more time than the three-node cooperation. Similarly, if a simulation allow four nodes to cooperate together, then it is certain that any configuration of the five-node

group required more transmission time than the four-node cooperation. In the case where three-node cooperation is used, other hops could be of paired nodes cooperation or of simple peer-to-peer relaying, as long as such hop and combination of cooperative nodes uses the least amount of resources. Using this criteria, the capacity bound can only improve by allowing more nodes to cooperate together as relay nodes.

Use t_{ref} to represent the time required for a source node to send directly to the destination node in a single hop. This reference time can be described as inversely proportional to the capacity link between the source and destination nodes. Assuming only one bit was sent, this relationship can be expressed as:

$$t_{ref} \propto \frac{1}{C_{i,j}}. \tag{4.10}$$

In the scenario where phantom nodes are used, the time a source node takes for this route is t_{route}. Where t_{route} is the smaller of the two time segments the source node takes to transmit to a single node or the phantom node,

$$t_{route} = min[t_{single}, t_{phantom}]. \tag{4.11}$$

Thus, for each hop between the source node to the intermediate node or the destination node, sum up the transmission time in which the source node requires to transmit its packet to the intended recipient:

$$t'_{route} = \sum t_{route}. \tag{4.12}$$

Once we find the total t_{route} value for all paths, or t'_{route}, take the smaller of the two between t_{ref} and t'_{route}:

$$t_{total} = \sum_{l=1}^{N} min[t_{ref}, t'_{route}]. \tag{4.13}$$

The total capacity of the network is the total amount of traffic the network needs to transmit, over the minimum time the network requires to transmit all the packets.

The total capacity of the network is denoted by:

$$C_{network} = \frac{\sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} t_{i,j}}{\sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} t_{i,j} t_{total}(i,j)}. \tag{4.14}$$

4.4 Results

All simulations use the network model as defined in chapter 2. This lower bound also used the same propagation model with impairments consist of path loss model, flat multi-path fading, and lognormal shadow fading with standard deviation of 6dB as with the information theoretic upper bound. The ten trials used for this simulation are identical to the ten trials used for simulating the information theoretical bound for comparison purposes. For this lower bound, 9-node networks and 25-node networks are used, but only results for the 9-node and 16-node networks are shown in this chapter. The result for the 25-node network with Uniform traffic matrix can be found in [6] and with Poisson traffic with mean 10 in [4]. The traffic matrix used Poisson traffic with mean 10. Figure 4.2 shows the 9-node network with two, three, and four node cooperation under a simple time-share bound model. The cases with node cooperation show significant improvement over the peer-to-peer result shown with a solid line, however, the improvement is negligible for any bounds using greater than paired nodes cooperation. Figure 4.3 shows a zoomed in view of the higher order node cooperation because the improvement was not visually detectable from Figure 4.2.

Similarly, Figure 4.4 has the same set up as the 9-node network presented in Figure 4.2 but with a 16-node network. However, the improvement is also negligible; adding extra nodes for cooperation does not significantly affect the capacity bound for both the 9-node network and the 16-node network scenarios. Numerically, three-node cooperation versus two-node cooperation has a slightly better improvement for both networks.

The simulation shows that the lower bound without frequency reuse performed worse than the information theoretic upper bound used as a yard stick. More impor-

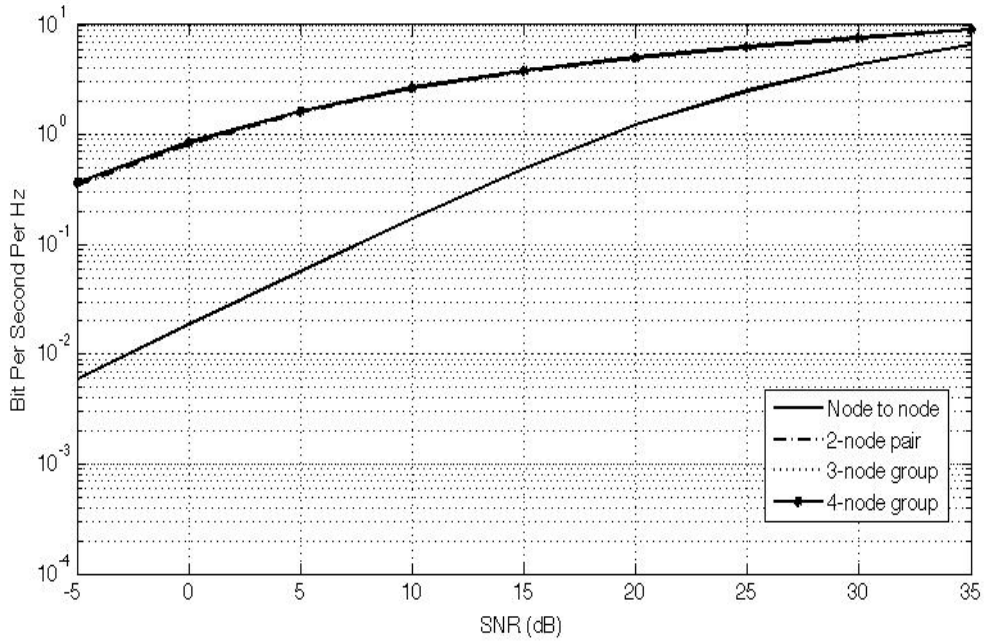

Figure 4.2: 9-node network with cooperation (with shadow fading)

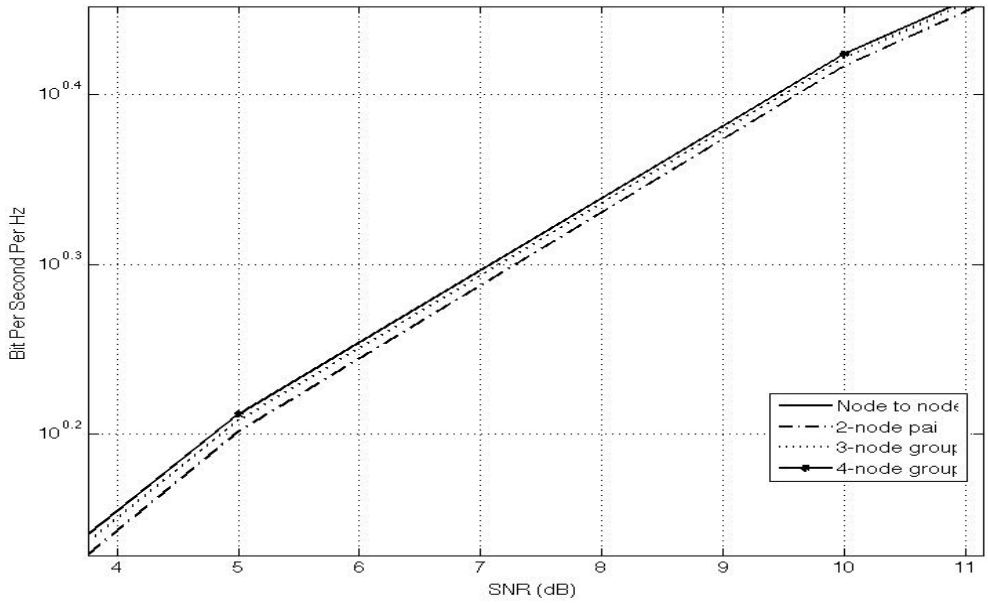

Figure 4.3: Close up view of the 9-node network with cooperation (with shadow fading)

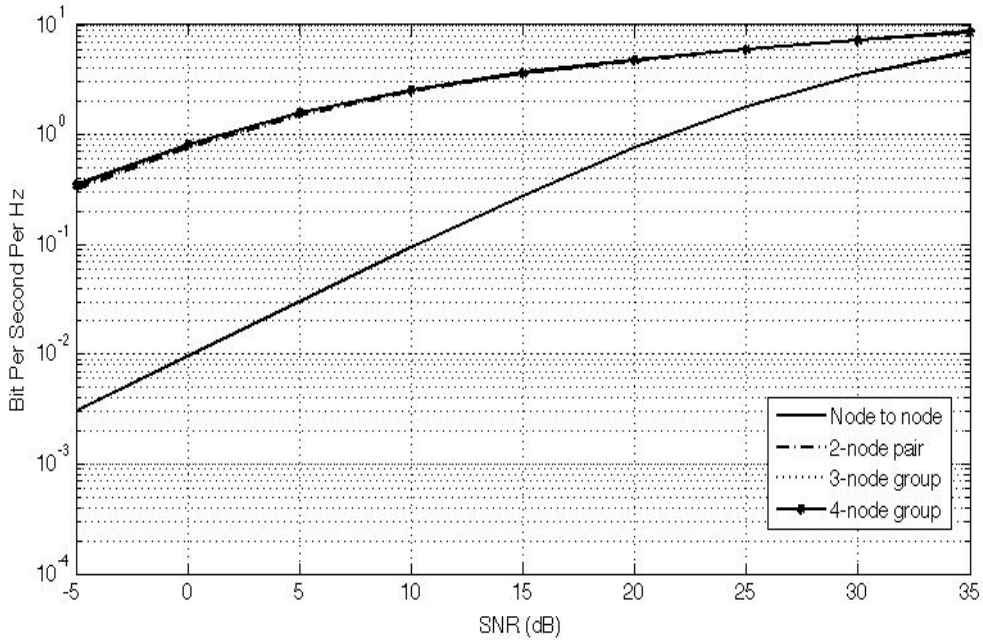

Figure 4.4: 16-node network with cooperation (with shadow fading)

tantly, the results show that cooperation with two-node pairs significantly improved the overall network capacity under the same scheme. However, allowing more nodes to cooperate together does not necessary improve the network performance. The method used in picking the number of nodes to cooperate would only improve the network capacity with more nodes grouped together, yet the capacity gain is not significant beyond grouping two nodes together for cooperation. In fact, the ratio of the network capacity for three or more nodes cooperation over paired nodes cooperation is roughly equal to one. Tables 4.1 and 4.2 show the performance ratios for different grouping of nodes.

This result is significant because future study can now focus on improving network capacity with using only two-node pair in any cooperation schemes. The software aspect of using more than two nodes is complex and might not be worthwhile. Synchronization between cooperating nodes also become more difficult as there is a need to consider more variables with added nodes.

Numerically, the ratio between three-node versus two-node group for cooperation is almost one-to-one. In other words, there is almost no gain in adding an extra node for

Table 4.1: Lower bound with a time-share scheme for 9-node networks, comparison shown with paired nodes performance over peer-to-peer (column 2), three-node cooperation over paired node (column 3), and four-node group cooperation over paired node (column 4)

SNR	$\frac{2-node}{1-node}$	$\frac{3-node}{2-node}$	$\frac{4-node}{2-node}$
-5	58.7165	1.0366	1.0527
0	43.8046	1.0271	1.0401
5	27.6125	1.01566	1.0242
10	15.0174	1.0111	1.0161
15	7.6950	1.0069	1.0096
20	4.1053	1.0068	1.0091
25	2.4936	1.0042	1.0053
30	1.7485	1.0025	1.0030
35	1.3801	1.0018	1.0022

Table 4.2: Lower bound with a time-share scheme for 16-node networks, comparison shown with paired nodes performance over peer-to-peer (column 2), three-node cooperation over paired node (column 3), and four-node group cooperation over paired node (column 4)

SNR	$\frac{2-node}{1-node}$	$\frac{3-node}{2-node}$	$\frac{4-node}{2-node}$
-5	104.1374	1.0685	1.0938
0	79.1336	1.0544	1.0731
5	50.0112	1.0368	1.0494
10	26.6239	1.0246	1.0325
15	12.9002	1.0149	1.0196
20	6.2392	1.0095	1.0125
25	3.3124	1.0066	1.0086
30	2.0616	1.0043	1.0058
35	1.5088	1.0028	1.0038

cooperation. The same is also true for four-node cooperation. Table 4.2 shows the ratio between paired node cooperation over peer-to-peer in the first column immediately to the right of the SNR values for a 16-node network. This table also shows the ratio between the throughput of 3-node cooperation over the throughput of paired node cooperation, and the throughput of the four-node cooperation over the throughput of a paired node throughput.

Both Tables 4.1 and 4.2 indicate that the greatest gain with paired node cooperation over the peer-to-peer is when the SNR is extremely low. This gain rapidly drops as SNR increases. At the highest SNR considered for the simulation, the gain is roughly 30 to 50 percent better than the peer-to-peer configuration. Even with this amount of gain,

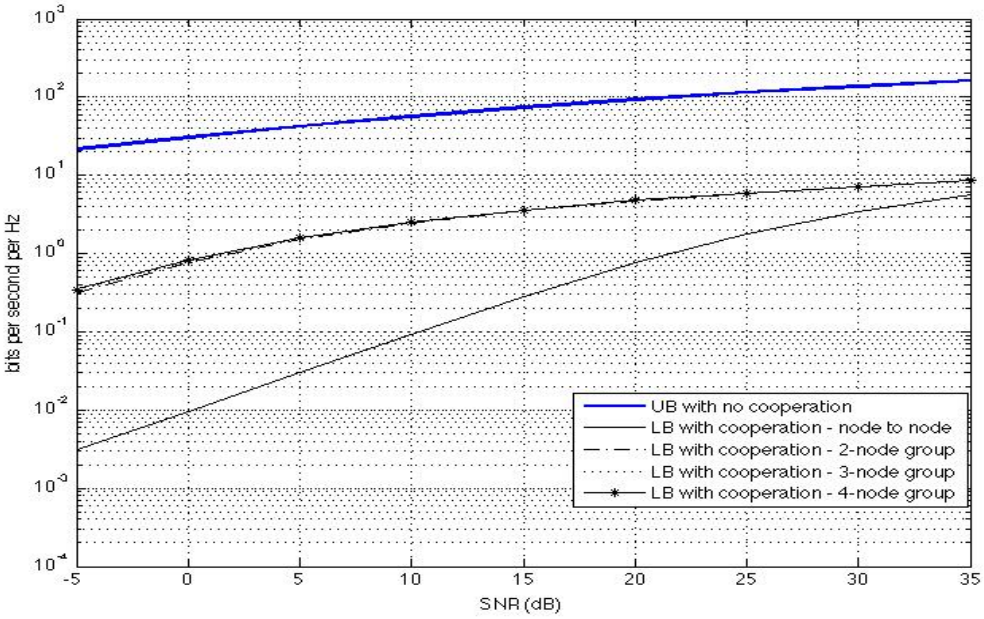

Figure 4.5: Lower bound without frequency reuse versus upper bound with frequency reuse for a 16-node network.

the result from the information theoretic upper bound is much greater that this lower bound with cooperation. This lower bound has no hope of achieving a similar network throughput as the upper bound.

4.5 Conclusions

For this simulation, an exhaustive search for the best path and the optimal number of nodes used for cooperation based on the minimum time requirement to transmit a packet is used. A separate capacity matrix is generated for each case with different number of nodes cooperatively relaying together. The traffic matrix also expands to keep record of the traffic elements for phantom nodes. This scheme is not expected to outperform the information theoretic upper bound because it does not include frequency reuse. From the simulation, the results show that performance significantly improved by adding paired node cooperation into the model. However, utilizing more nodes for cooperation did not provide significant improvement over the paired node cooperation.

This is shown in Figure 4.5, where a 16-node network with propagation impairments of path loss, multi-path fading, and shadow fading are considered for both the upper and lower bounds. All capacity curves are an average of 10 independent trials. It is also observed that the benefit of using node cooperation diminishes as SNR increases. The gain from node cooperation is most prominent at low SNR. This is because the effects of the imperfection of the channel diminish with higher SNR.

The major contributions of this chapter are (1) the simulation justifies in not using higher order node-cooperation beyond paired node cooperation and (2) there is no hope in outperforming the highly optimistic information theoretic upper bound with the simple time-share scheme. The first discovery is significant in that adding higher order of node-cooperation returns minimum gain but added extra complexity for node synchronization. The extra node added for cooperation also would require to exert its limited battery power to help relay the packet for very little network throughput gain. The ratio of improvement on average for a 9-node network is .0153 (average of the ratios for the 3-node and 4-node cases) and is at best 0.094 times better than paired node cooperation when using the four-node cooperation scheme with negative SNR. Depending on the transmission bandwidth, it might be worthwhile for some applications, but the additional overhead needed to add an extra node for cooperation might make the gain insignificant.

The confirmation provided by (2) is also significant. Many older applications used in communication still employ time-share algorithms. Even as the research trend has started moving toward cooperation, companies are working to incorporate cooperation with their outdated time-share schemes. This simulation showed that time-share scheme could never outperform the original peer-to-peer network even with node cooperation. Other transmission protocols must be used in junction with node cooperation in order to achieve optimal network throughput for wireless ad hoc networks.

For the results of the simulation, there is much room for improvement and simply adding frequency reuse might not be enough for the lower bound with node cooperation to catch up to the information theoretic upper bound. However, this lower bound is

achievable while the information theoretic upper bound is not. It is almost certain that the upper bound calculated and simulated is too optimistic. While other researchers showed that receiver cooperation helps achieve better network throughput, this topic is not covered in this dissertation. Rather, frequency reuse was incorporated into the model instead, providing a more realistic model of real network transmission.

Chapter 4, in part, has been submitted for publication of the material as appeared in the following papers: Anthony S. Acampora and Louisa P.S. Ip. "A Lower Bound on the Capacity of Wireless Ad Hoc Networks with Cooperating Nodes," Ad-Hoc NOW 2008, LNCS 5198, pages 230-240, September 2008, and Anthongy S. Acampora and Louisa P.S. Ip, "Comparison of the Lower Bound for the Capacity of the Wireless Ad Hoc Networks with Cooperating Nodes to the Upper Bound of Conventional Peer-to-Peer Wireless Networks with Hop-by-Hop Routing," Ad Hoc and Sensor Wireless networks: An International Journal," 9(1-2):73-84, 2010. The dissertation author was the primary investigator and co-author of these papers.

Chapter 5

Lower Bound of Wireless Ad Hoc Networks With Node Cooperation and Frequency Reuse

5.1 Introduction

Previously, the lower capacity bound of a wireless ad hoc network with two or more nodes transmitting in cooperation was determined. A simple time-share bound with no frequency reuse is used. This bound indicates the benefits of using node cooperation diminishes as the SNR increases, and there is no significant gain in the network throughput by allowing more than two nodes to cooperate together. It is not worthwhile to add on extra complexity in order to allow more nodes to cooperate together. However, the results showed significant capacity gain by using paired node cooperation over peer-to-peer relay routing in the scenario of no frequency reuse, in the case with transmitters cooperation only and without receivers cooperation. Ng et al. [32] suggested that transmitter cooperation outperforms receiver cooperation when the cooperation channel is strong. The reverse is true when the cooperation channel is weak. Combining transmitter and receiver cooperation provides greater gain than transmitter-only or receiver-only cooperation. Transmitter and receiver cooperation is definitely high in the priority list. However, to improve the network throughput, frequency reuse might have a much bigger impact than incorporating receiver cooperation to the previous time-share model. Therefore, instead of focusing on modeling receiver cooperation, attention is placed on adding frequency reuse to the model. Using the simple time-share model to determine the network throughput is not sufficient, nor realistic in today's application.

The purpose of frequency reuse is to increase the capacity by reusing the same frequency band in different areas of the network for a different set of transmission. There are numerous coding schemes in the field exploiting frequency reuse in cellular networks that could be extended to ad hoc networks. While it is not the focus here to analyze the schemes, some notable ones are briefly mentioned; they could be used as tools to implement a practical system to achieve the bounds derived and simulated in this chapter. A simple example is a cellular network that uses code division multiple access (CDMA). CDMA uses spread-spectrum technology and orthogonality so that multiple nodes may access the same physical channel simultaneously. Spread-spectrum

technology is a matured scheme, highly employed by military communication devices to resist against jamming and it is resistant to multi-path fading. There are two different types of CDMA, frequency hopping and direct sequence. Andrews et al. [8] argues that CDMA does not inherently improve the spectral efficiency of ad hoc networks because of the interference averaging can not be fully appreciated by the irregular locations of the transmitters and receivers. However, they also agreed that frequency hopping and direct sequence do provide some advantages. The authors listed a few advantages of using CDMA in the ad hoc networks environment and also some disadvantages. Advantages include longer hops, overcoming narrowband fading, avoiding hidden nodes problem, and also providing an added layer of security by making eavesdropping more difficult. Disadvantages include interference averaging is ineffective as mentioned above as the major issue and the overhead in keeping track of the current position of the sequence for time synchronization does not justify for a mobile network with bursty traffic. However, CDMA will require further study to determine if the pros outweights the cons.

Another technique for exploiting frequency reuse is location based clustering for mobile nodes [42]. For this scheme, access points or gateways/base stations are needed to make interference measurements over the carrier frequency. The purpose is to ensure there is sufficient separation between two access points that are using the same channel. The scheme has been applied to military related operation in the past; this is a significant sign that such a technique could be made available to commercial world in the near future, as with Aloha Net that started for military use, or the power electronic building blocks program started by the Office of Naval Research, with intention of extending to the commercial world such as the hybrid electric vehicles.

There are other researchers interested in discovering optimal frequency reuse for ad hoc networks. Jindal presented at Rice University's Center for Multimedia Communication seminar on "Optimizing Frequency Reuse in Ad-Hoc Networks" in February 2007. He also collaborated with Andrews on related topics. This area is not yet matured, but the interest is there.

The research done here is not basing on CDMA, time-division multiple access

(TDMA), frequency-division multiple access (FDMA), or other interference avoidance strategies. Here, when nodes are transmitting, they use the entire spectrum with no spread spectrum coding or frequency selective coding. Rather, the only attempt to avoid interference is by selecting nodes simultaneously sending to meet certain interference criteria.

The following sections are organized such that the network model with interference is presented immediately after the Introduction. Next, the routing algorithm used to determine how nodes can transmit at the same time is explained. Finally, results are compared against the previous lower bound with no frequency reuse. There is a slight improvement as the result of adding frequency reuse to the model but the gain diminishes as SNR increases. Comparing these results with the information theoretical upper bound with frequency reuse, the gain decreases with the larger network of 16 nodes. The conclusions highlight some observations based on the results and recommended some future directions. While node cooperation is still relatively new in the history of communication, initial research indicates that node cooperation works well with a small subset of nodes and performance gain decreases for larger networks.

5.2 Network Model

The network model for finding the lower bound with frequency reuse is similar to the network model described in chapter 2 with a modification. Consider a network with N nodes scattered randomly in a square service region. If the nodes were uniformly spaced in the region separated by distance d apart, where d is the length L of the service area divided equally by the number of nodes $N-1$. Similar to equation 2.1:

$$d = \frac{L}{\sqrt{N}-1}. \tag{5.1}$$

The results obtained using this configuration is defined as normalized signal to noise ratio, ρ, such that in the absence of fading and interference. The random scattering of nodes is proportionally scaled to maintain this fixed distance relationship to obtain

results in normalized SNR.

Assume each node uses P watts for transmission, the modified version of Shannon theorem with interference plus noise is given by:

$$C \geq W \log \left(1 + \frac{P}{NW + P'}\right). \tag{5.2}$$

As with the case with no frequency reuse, the bandwidth is set to one hertz such that the results obtained here are in per hertz. The diagonal of the capacity matrix will always be zero because no node may send a packet to itself. This equation can be generalized to more than two transmitters by summing up all other transmitter's transmission power:

$$C \geq W \log \left(1 + \frac{P_i}{N_i W + \sum_{j \neq i} P_j}\right). \tag{5.3}$$

P_j represents the transmitting power by other sending nodes within hearing distance of node i. Interference generated by other sending nodes has a negative effect on the link capacity between node i and its intended destination.

This link capacity element represents the point-to-point Shannon capacity based on signal-to-interference plus noise ratio. The interference is kept to the minimal based on the routing algorithm described in section 5.3. The selected nodes allowed to transmit together have minimum effects on the other sending nodes. For each node discovered and added to this transmitting group, the overall throughput or combined capacity must be greater than the case without the node. The capacity matrix represents the maximum rate at which a packet can be transmitted between a pair of nodes with co-channel interference.

There is a separate capacity matrix for paired node cooperation. In other words, a capacity matrix is defined for the peer-to-peer link and a separate capacity matrix is created for the case where two nodes are cooperating as a relay node.

The propagation model consists of path loss, multi-path fading and shadow fading. These propagation impairments will effect the SNR as shown in the previous lower

bound and upper bound models, reiterated below:

$$\rho_{i,j} = \rho \left(\frac{d}{R} \right)^4 e^X 10^{\frac{\epsilon}{10}}. \tag{5.4}$$

The SNR is recalculated when a new node is added to the selected group of transmitting nodes for parallel transmission. The capacity matrix is updated with new SNR values before finding another node to be added to the group. The capacity for when a node is sending to a phantom node is based on the worst case; the smaller of the two capacity elements. The capacity link from node i to nodes $\{j,k\}$ is defined as:

$$C_i^{j,k} = min\{C_{i,j}, C_{i,k}\}. \tag{5.5}$$

In the case where two nodes are cooperatively sending packets to a single node, the respective SNR must be recalculated. Repeating from the lower bound without frequency reuse, for two nodes sending with P watts or square root of P in volts, add the two voltages together and take the square of the resulting voltage to obtain watts. For example, node j and node k would like to send a packet cooperatively to node i,

$$v_{jk}^i = v_{j,i} + v_{k,i} = \sqrt{P_{j,i}} + \sqrt{P_{k,i}}. \tag{5.6}$$

Taking the square on both side to obtain power in watts,

$$\rho_{j,k}^i = (v_{j,k}^i)^2 = \left(\sqrt{P_{j,i}} + \sqrt{P_{k,i}} \right)^2. \tag{5.7}$$

Regardless if the transmission is one node to two nodes or two nodes to one node, the capacity link must then be calculated as indicated in equation 5.2 or 5.3 for each round of node selection to transmit simultaneously.

The relative traffic matrix from equation 2.7 that defines the exogenous traffic between the source node and the destination node is also used here. This relative traffic matrix will expand as phantom nodes are being added to the network. It is used each time the system must rediscover a new set of nodes for parallel transmission. The transmitter

with the largest traffic element will be selected as the "seed", in which additional nodes added to the group for parallel transmission must satisfy the criteria that a new node is added if and only if it improves the overall capacity.

5.3 Routing Algorithm

Rather than recalculating the transmission path again, the model from the previous time-share bound is modified to record the paths it used for the no frequency reuse bound. Each path from the source node to the destination node and via any relay nodes in between is the optimal path in the absence of interference. The search criteria for finding nodes that may transmit simultaneously requires that the selection would create the least impact to the other sending/receiving nodes. By doing so, it is reasonable to use this interference-free path and ensure convergence at the end. The issue of convergency for a fully decentralized network is discussed in the chapter on future directions.

There are two steps in the routing process; transmit node selection and how packets may be transmitted for each hop. Between each round of finding nodes that may transmit in parallel, the SNR between nodes and the capacity matrix must be updated. The traffic matrix must be updated for each hop to monitor the flow of traffic. The matrix dimension could be growing as more phantom node pairs are used.

The first node picked as a transmitting node has the greatest amount of traffic to send. This is also known as the "seed" node. The next node selected is based on the amount of degradation it would cause to the seed node and to itself, caused by the interference from the other node. The algorithm selects an additional node that may transmit at the same time as the first selected transmitting node, where the second node may only cause a maximum degradation of $\frac{C}{M}$. M being the number of nodes sending in parallel, or $M = 2$ in this case, and C is the capacity link for the transmitting nodes. After a round of exhaustive search and selecting all potential nodes that meet this criteria, the node that contributes the highest total capacity is picked. The capacity matrix is updated with the assumption that these two nodes are transmitting. The selection

of the third node for simultaneous transmission is determined by repeating the search method described. If there are no other nodes that meet the criteria for transmission, the selection process ends here. The two nodes selected would transmit at the given time slot as defined later in this section. When one of the two transmitting nodes has completely sent its packets to the destination node, the whole process of transmit node selection repeats again even if the second node has not yet transmitted all the intended packets to its destination. The remaining packets are stored in the last relay nodes for future transmission.

An equation can describe the fundamental relationship for the scenario where node i is the node with the greatest traffic elements intending for destination node j. Node k with traffic intended for node l meets the criteria of restricting the maximum degradation to $\frac{C}{M}$ and also provides the least amount of interference compared to other nodes that also meet the criteria:

$$C_{i,j} < C'_{i,j} + C'_{k,l}. \tag{5.8}$$

Therefore adding transmitter k intended for destination node l has a positive effect on the original capacity of node i sending to node j. This equation can be extended for the three parallel transmitting nodes case:

$$C'_{i,j} + C'_{k.l} < C''_{i,j} + C''_{k.l} + C''_{m,n}. \tag{5.9}$$

It is important to note that a node may not transmit and receive at the same time. Therefore, the transmitter cannot be sending to a receiver that is already a recipient of another transmitting node or is a transmitter itself for this time slot. It is also important to look up the predetermined path to ensure that the next hop of this transmitting node is not already been used. For paths requiring a paired node as the next hop, both nodes in the pair must be checked. This requirement is described in greater detail later. The concept described above is relatively simple but difficult to simulate. Intensive bookkeeping is necessary and the simulation is time consuming.

The capacity matrix must be re-calculated during the search. This is because the SINR is different for each combination of transmitting nodes. The capacity matrix should be updated based on equations 5.2 and 5.3 for each hop.

An exhaustive search for the next potential node for simultaneous transmission would bring the order of operation to $(N-2)^{(N-3)}$. It is therefore not practical for a large network. It is possible to reduce this exhaustive search by using a random selection of the next node transmitting, and finding the best link to its possible destination. For this routing algorithm, first randomly pick a node that is not currently sending or receiving and examine all possible destinations. The source and destination pair that returns with the least amount of interference to the original sending node (or nodes) would be added to the group for simultaneous transmission. This process can be repeated to add more nodes to be transmitted at the same time. However, to be sure that the results are based on the best possible combination of transmitting nodes, the exhaustive search algorithm is used.

The duration of each hop is determined by the fastest capacity link of the transmitting nodes, or

$$t_{shortest} \propto \frac{1}{C_{highest}}. \tag{5.10}$$

It is possible that the other transmitting node or nodes might not have enough time to transmit all its traffic. In that scenario, a fraction of packets based on time allotted is transmitted. The rest of the packets must wait until the next hop.

Say if node i's traffic is intended for node j, node k's traffic is intended for node l, node m's traffic is intended for node n, and node o's traffic is intended for node p. The time allowed for this transmission is the least time required for this one hop with this selected group of nodes for simultaneous transmission, or identified as t_1 in Figure 5.1. Each transmitting node would follow the predetermined path to perform this one hop. If the predetermined path for node i is to directly send to node j, the transmission will use the direct hop. At the same time, if the predetermined path for

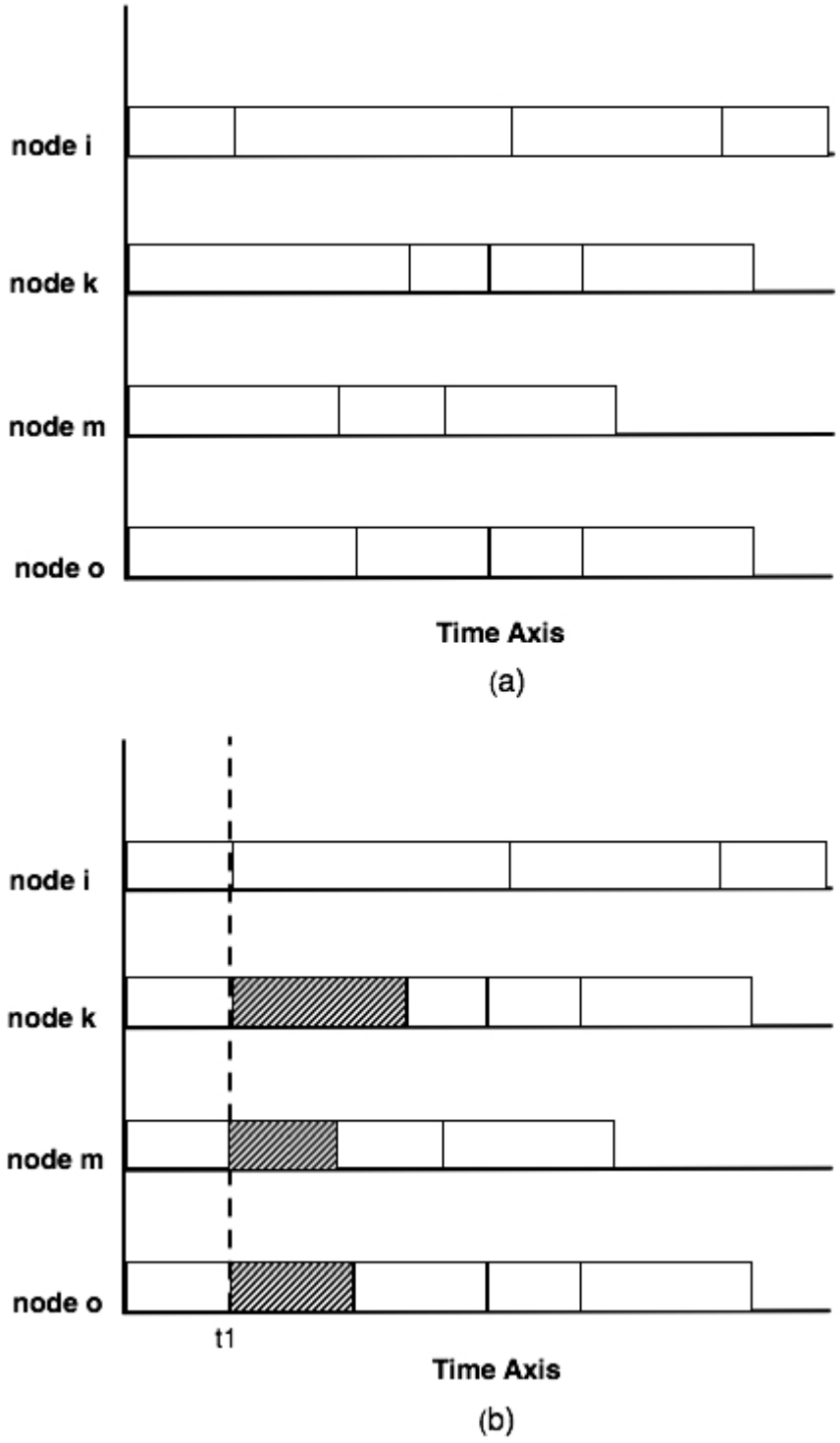

Figure 5.1: Sample method of determining time allowed per hop, (a) original traffic, (b) packet divided to within a given time slot for transmission.

node m is to transmit to node x and y, it will send whatever traffic allowed during the time allotted to node x and y, and queue the remainder of the traffic until the next hop. In this case, because node i has already transmitted its intended packets to node j in a direct single hop, a new selection of simultaneously transmitting nodes will be selected. Node m will only be allowed to transmit the rest of the packet if it is selected based on the transmitting nodes selection algorithm described earlier. On the other hand if the predetermined path for node i is to transmit to say node z, instead of node j, and no other nodes have completed their transmissions to their intended destination node, the same group of nodes (or rather, the intermediate nodes, since this group of nodes have already transmitted their traffic to their intermediate relay nodes), will continue the transmission until the traffic reaches one of the intended destination nodes.

The total time required to allow all traffic elements of the selected parallel transmitting nodes to flow through the network is the sum of the minimum time needed for each transmission hop:

$$t_{min} = t_1 + t_2 + ... + t_n. \tag{5.11}$$

t_n is when the last element of the selected group flows to its destination node. The network capacity for this model is the sum of all traffic elements that must flow to their respective destination nodes over the total minimum time required to transmit all such traffic elements:

$$C_{network} = \frac{\sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} t_{i,j}}{\sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} t_{i,j} t_{min}}. \tag{5.12}$$

The routing algorithm is relatively straight forward and the difficulty in this simulation is in the coding. Figure 5.2 shows a basic block diagram of the steps in updating the capacity matrix and in finding nodes for parallel transmission. The process starts at the upper left hand corner and the series of steps were repeated until all traffic flows through the network.

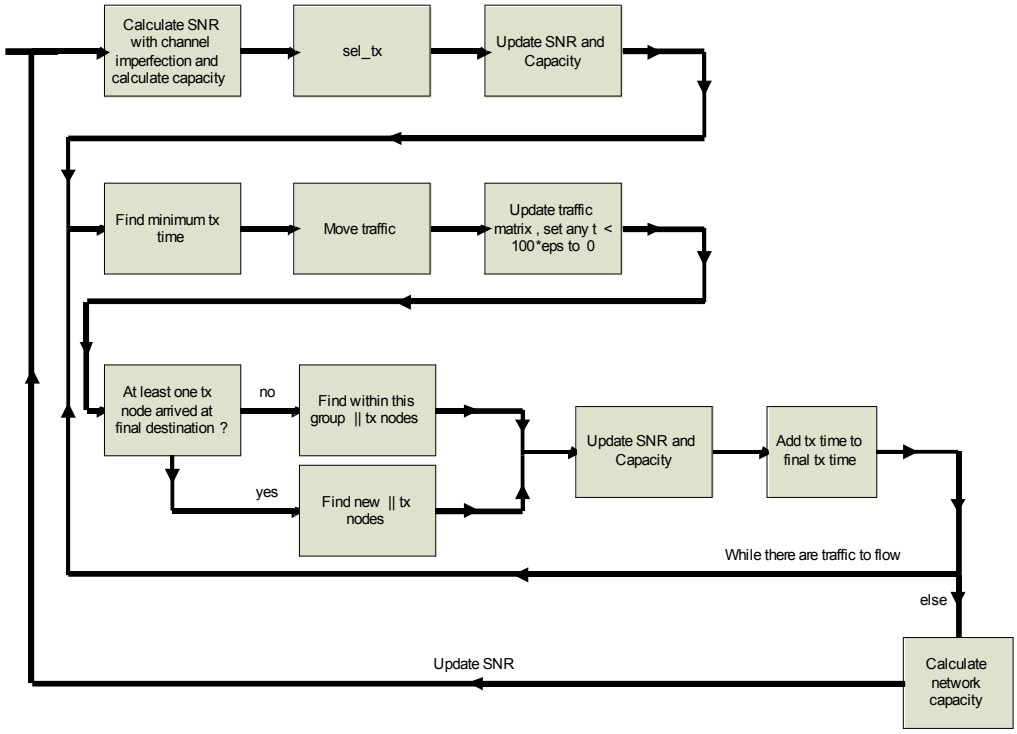

Figure 5.2: Block diagram

5.4 Results

For each variation of the upper bound and lower bounds with and without frequency reuse, a simulation of 10 trials are averaged together to obtain each curve. The random placement of the nodes are consistent across the upper bound and lower bounds with and without frequency reuse. The capacity matrix, the traffic matrix, and the propagation model are also constant throughout each type of bounds, differently only across the 10 trials.

Figure 5.3 shows the performance comparison between the upper bound and lower bounds with and without frequency reuse, and when different number of nodes cooperatively relay together. The propagation impairments includes path loss, multi-path

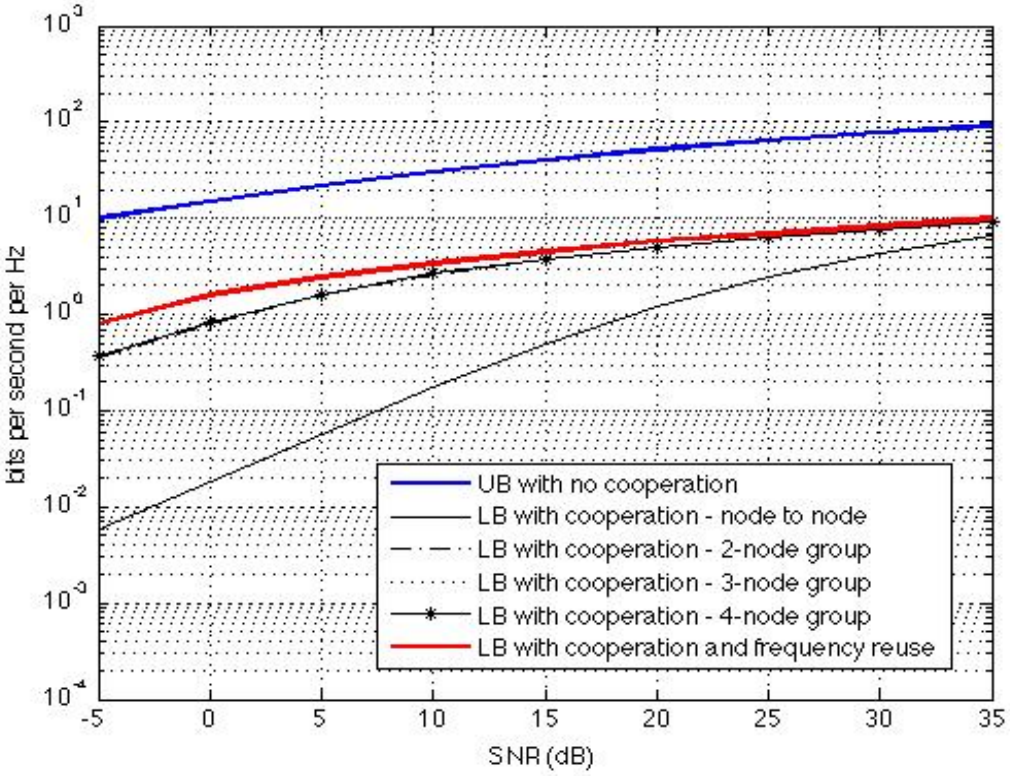

Figure 5.3: 9-node network with upper bound (UB) without cooperation, with frequency reuse versus lower bound (LB) with node cooperation, with time-shared scheme and with frequency reuse scheme. The results of paired node, three-node, and four-node cooperation is shown for the LB using the time-shared scheme.

fading, and shadow fading. By including cooperation, the overall network performance improved, and there is also a gain by including frequency reuse into the model. Unfortunately, the gain from including frequency reuse is not as significant as hoped. The gain diminishes as the SNR increases, making cooperation useful for noisy environments but not as beneficial in a relatively noiseless environment.

Figure 5.4 shows a closeup view of the capacity bound for the paired node, three-node, and four-node cooperation. The upper bound, the peer-to-peer lower bound using time-shared scheme, and the lower bound with paired node cooperation using frequency reuse scheme are out of the display range. Due to the algorithm employed here in which adding extra nodes for cooperation must improve the overall network capacity,

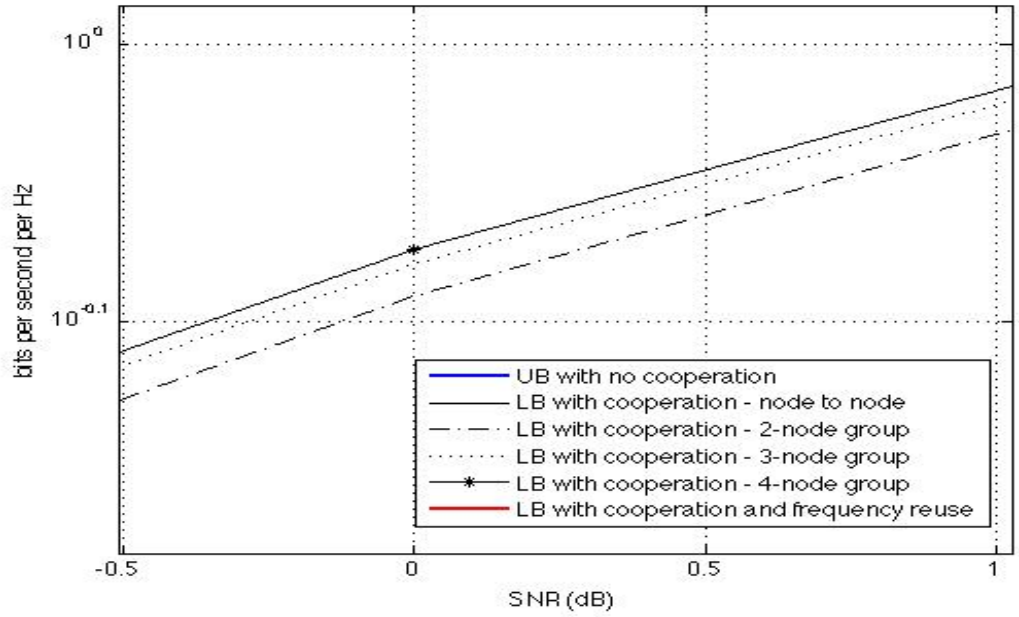

Figure 5.4: Close up view of the 9-node network's lower bound (LB) with node cooperation, using frequency reuse scheme for paired, three- and four-node cooperation. The upper bound, the peer-to-peer lower bound using time-shared scheme, and the lower bound with paired node cooperation using frequency reuse scheme are out of the display range.

the capacity bound is the highest for the 4-node cooperating group. The same trend goes for 5-node and 6-node cooperation, but are not shown here since they add little value to the final results.

Figure 5.5 is the same simulation as with Figure 5.3 but for a 16-node network. There was a greater gain in the 16-node network than in the 9-node network. A bigger network also allows additional nodes to cooperate and transmit together. However, its performance compared to the information theoretic upper bound with frequency reuse is still out of reach. The upper bound for the 16-node network is also much greater than the 9-node network. The gap between the upper bound and lower bound with frequency reuse and node cooperation is greater for the 16-node network than the 9-node network.

Numerically, the ratios between the upper bound versus lower bound with and without frequency are shown in Tables 5.1 and 5.2. These tables indicate the ratios

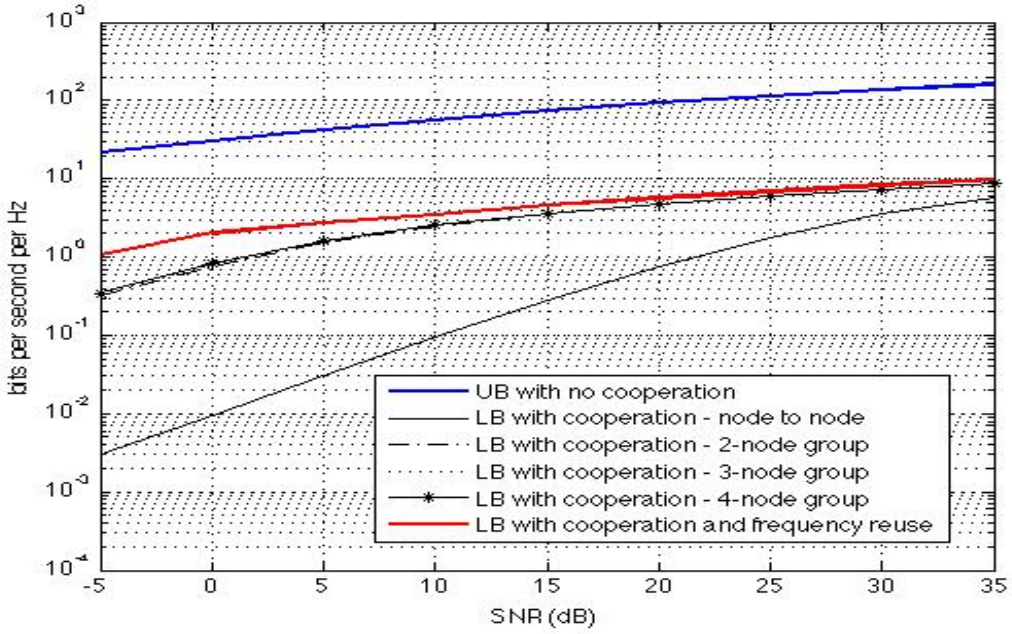

Figure 5.5: 16-node network with upper bound (UB) without cooperation, with frequency reuse versus lower bound (LB) with node cooperation, with and without frequency reuse.

between the upper bound performance over the lower bounds for the time share bound and the frequency reuse bound.

Neglecting the first two SNR results since the signal is hidden in noise, there is an interesting trend that is present in both sets of simulations with frequency reuse and

Table 5.1: 9-node network, presented in a ratio between the upper bound performance over the lower bounds with frequency reuse or with time-share for column 2 and 3 respectively.

SNR	With Freq Reuse	Time-share
-5	12.469	28.991
0	9.391	18.557
5	8.849	13.655
10	8.859	11.576
15	8.930	10.715
20	9.047	10.448
25	9.403	10.350
30	9.517	10.299
35	9.323	10.244

Table 5.2: 16-node network, presented in a ratio between the upper bound performance over the lower bounds with frequency reuse or with time-share method for column 2 and 3 respectively.

SNR	With Freq Reuse	Time-share
-5	20.431	67.623
0	14.944	39.999
5	15.208	27.808
10	16.147	22.703
15	16.095	20.554
20	16.337	19.677
25	16.538	19.265
30	16.584	19.005
35	16.579	18.780

node cooperation. A monotonic increase in the ratio is observed until approximately 30dB. This indicates that the upper bound is performing increasingly better over the frequency reuse case as SNR increases. At around 30dB, there is a slight decrease in the ratio, indicating a turnaround point that the lower bound is improving against the upper bound. This is interesting because as SNR increases, the more likely nodes could interfere with one another during simultaneous transmission. Therefore, less nodes may simultaneously transmit together as SNR increases and the trend would slowly approach to peer-to-peer, hop-by-hop routing. Interestingly, from previous results for the time-share bound, it is true that as SNR increases, the benefits of using two or more nodes diminishes. Thus, the trends indicate as SNR increases, the models follow in the same results as peer-to-peer, hop-by-hop case with no cooperating nodes. More points in the SNR axis would help in determining the consistency of this trend. This trend is persistent in both the 9-node and the 16-node networks.

5.5 Conclusions

The lower bound for node cooperation and with frequency reuse was presented. The basis of this simulation was held constant for the upper and lower bounds, meaning the same random scattering of nodes, the same traffic matrix, the same capacity matrix, multi-path fading, and shadow fading are held constant for all three cases, varying only

for the ten trials used for repeatability. By doing so, the effects of node cooperation and frequency reuse are isolated from other factors. It is observed that node cooperation alone with or without frequency reuse could not outperform the information theoretic upper bound. In fact, the more nodes in a network, the greater the gap there is between the upper and lower bounds as the SNR increases. It is unfortunate that cooperation could be limited to small networks and its scalability is limited. The improvements due to node cooperation and frequency reuse also diminishes with higher SNR up to a certain point. For this case, it is observed that the trend of how well the upper bound outperformed the lower bounds peaks out at around 25dB. A decreasing trend is observed from 30dB and higher. This observation is consistent with the fact that with increasing SNR, less nodes may transmit simultaneously as interference increases. These bounds approach the peer-to-peer, hop-by-hop case as SNR increases. For high SNR, the bound with node cooperation approaches the bound without node cooperation. However, in a fading environment, node cooperation could only help with the transmission. If the fading is strong and transmission with node cooperation failed, there is little to no hope for a direct transmission to achieve what node cooperation utilizing spatial diversity could not.

The upper bound here is highly optimistic. It does not consider interference nor is it achievable in the real world. The gap between these bounds might not be as pessimistic if interference was included in the upper bound. More importantly, results showed that node cooperation does improve overall network throughputs up to a certain SNR threshold. It could be of value to simulate this model at a higher set of SNRs to determine if this trend holds.

Chapter 5, in part is currently being prepared for submission for publication of the material. The dissertation author was the primary investigator and author of this paper.

Chapter 6

Conclusions and Future Directions

In this dissertation we have made three major contributions. First, information theory is applied to a switching network to determine an easily computable upper bound. This bound is generated by finding a scaling factor for the relative traffic matrix by comparing the rate switching decisions must be made by the network against the maximum rate at which the network can make routing decisions. By scaling the traffic matrix with this scaling factor, the optimal capacity of the network is derived. This is a highly optimistic bound and it is useful for future comparisons against any lower bounds derived.

Second, the lower bound with multiple nodes cooperation is simulated. The results showed that paired node cooperation provides significant gain over peer-to-peer network for the time-share bound. However, using more than two nodes for cooperation did not provide much gain. Depending on the transmission frequency, it might not be worthwhile to add extra complexity in order to add an extra node for cooperation.

Finally, the model with frequency reuse was presented. Based on the results from the time-share bound, this simulation used only paired node cooperation. Results show that even with frequency reuse, this lower bound could not possibly outperform the highly optimistic information theoretic upper bound. As the number of nodes increases in a network, the bigger the gap between the upper and the lower bounds. Therefore, cooperative networks might only be suitable for small networks. Another important observation made from this model is that as SNR increases, the gain from using cooperative nodes diminishes. In fact, at a higher SNR, there seems to be a trend in which cooperation slowly approaches to the throughput of a peer-to-peer network. However, in a fading environment, node cooperation could only help with the transmission. If the fading is strong and transmission with node cooperation failed, there is little to no hope for a direct transmission to achieve what node cooperation utilizing spatial diversity could not.

It is important to note that while the upper bound is of a theoretical study, the lower bounds are highly non-information theoretic. The results for the lower bounds are the results of specifying a set of standard propagation impairments and routing

strategies to generate a realistic and practical system. My professor who taught the honors mathematic series at the University of Washington once responded to my question of application with, "Ah! We have an engineer here!". Theoretical analysis has its merit, but as an engineer, practicality is always the main goal.

While there were many detours taken in this maze-like journey, there are still many more topics that I could have placed my focus on but did not. Walter J. Phillips once said, "no sincere artist was ever satisfied with his labour". This chapter is dedicated to those topics that I could have covered (in the world of unlimited computer resources, time, funding...), but took the other paths that were deemed more important at the time. It is my hope to further cover these topics perhaps with a postdoctoral position or with my colleagues at Stanford Research Institute.

There are some areas that are easy to achieve but rather time consuming. For example, having a super computer to generate the final results shown in Chapter 5 for larger networks could provide valuable insights on how cooperation affects such networks. However, given the technology at the time of simulation, generating results for a 25-node network would have taken about one week per trial. It took roughly 72 hours to generate one data point for the 25-node network at low SNR, and there are 9 data points per trial. From the simulations with 9-node and 16-node networks, the simulation took more processing time at lower SNRs than at higher SNRs. On average, two hours were required to simulate a single trial for the 16-node network, while only minutes were required for the 9-node network. It was not possible to simulate the network with 25, 64, and 100 nodes with the available equipment. Options were discussed; the University of Wisconsin's and Stanford Research Institute's Condor networks were considered. However, existing code must be parsed into standalone jobs and be compatible with the different versions of MatLab used by the computers within the Condor network.

Another improvement would be to extend the range of SNR to -35dB to determine if more than two nodes cooperating together has a significant improvement on the capacity bound over the paired node cooperation.

Finally, a quick search showed that localization using cooperative nodes was not

explored. While signal strength detection is not a reliable source of location tracking; connectivity using cooperative relay nodes could be. For paired node cooperation, a relay node may receive data points from the source, destination, and its partner node. There is a potential to use the setup to explore localization without adding extra hardware using node cooperation. Robots may use the collaborated information to rotate their data correctly and combine sensor data to map a 3D model of the environment. Algorithm analysis and a white paper is in progress; encouraged by a research group from SRI's Artificial Intelligence Center. Such idea is just one of many possible applications for cooperative networks.

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