Evaluation of Dynamic Channel and Power Assignment Techniques for Cognitive Dynamic Spectrum Access Networks

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(ABSTRACT)

This thesis provides three main contributions with respect to the Dynamic Channel and Power Assignment (DCPA) problem. DCPA refers to the allocation of transmit power and frequency channels to links in a cognitive dynamic spectrum network so as to maximize the total number of feasible links while minimizing the aggregate transmit power. In order to provide a method to compare related, yet disparate, work, the first contribution of this thesis is a unifying optimization formulation to describe the DCPA problem. This optimization problem is based on maximizing the number of feasible links and minimizing transmit power of a set of communications links in a given communications network. Using this optimization formulation, this thesis develops its second contribution: a evaluation method for comparing DCPA algorithms. The evaluation method is applied to five DPCA algorithms representative of the DCPA literature . These five algorithms are selected to illustrate the trade-offs between control modes (centralized versus distributed) and channel/power assignment techniques. Initial algorithm comparisons are done by analyzing channel and power assignment techniques and algorithmic complexity of five different DCPA algorithms. Through simulations, algorithm performance is evaluated by the metrics of feasibility ratio and average power per link. Results show that the centralized algorithm Minimum Power Increase Assignment (MPIA) has the overall best feasibility ratio and the lowest average power per link of the five algorithms we investigated. Through assignment by the least change in transmit power, MPIA minimizes interference and increases the number of feasible links. However, implementation of this algorithm requires calculating the inverse of near singular matrices, which could lead to inaccurate results. The third contribution of this thesis is a proposed distributed channel assignment algorithm, Least Interfering Channel and Iterative Power Assignment (LICIPA). This distributed algorithm has the best feasibility ratio and lowest average power per link of the distributed algorithms. In some cases, LICIPA achieves 90% of the feasibility ratio of MPIA, while having lower complexity and overall lower average run time.

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Chapter 1

Introduction

1.1 Motivation

In a Cognitive Network (CN), radios adapt their operating parameters to achieve network-wide objectives such as connectivity and efficient resource utilization [1]. In Dynamic Spectrum Access (DSA), a CN of spectrum agile radios must efficiently utilize spectrum resources throughout the network. Research on Dynamic Channel and Power Assignment (DCPA) seeks effective ways in which a CN of autonomous radios can select the appropriate frequency channel and transmit power to improve connectivity and spectral efficiency given available spectrum. Many DCPA techniques have been proposed in literature [2–8], and evaluating the tradeoffs among these techniques from the existing body of work is a difficult task. Each DCPA algorithm can be evaluated under different topologies, node densities, metrics, and channel conditions. Thus, these differences in the body of work make analyzing the tradeoffs among DCPA works problematic. With the renewed interest in DSA, assessing the tradeoffs among these DCPA mechanisms under a common set of evaluation parameters has become important.

1.2 Contributions

This thesis provides three main contributions with respect to the DCPA problem. In order to provide a method to compare related, yet disparate, work, the first contribution of this thesis is a unifying optimization formulation to describe the DCPA problem. Using this optimization formulation, this thesis develops its second contribution: a evaluation method for comparing DCPA algorithms. The evaluation method is applied to four DPCA algorithms representative of the DCPA literature based on the works of [3–6]. These algorithms were selected to illustrate the tradeoffs between different control modes and channel/power assignment techniques. In terms of control modes, algorithms based on [3, 5] are centralized, while the ones based on [4, 6] are distributed. The third contribution of this thesis is a proposed distributed channel assignment algorithm, LICIPA which combines aspects of [4, 6].

1.3 Outline

This thesis follows an unconventional strategy for describing related work. Rather than providing a chapter of related work, the thesis positions itself with respect to literature throughout. Chapter 2 introduces the system model used to analyze the DCPA algorithms and introduces the mathematical formulation of DCPA as an optimization problem. Chapter 3 identifies common DCPA mechanisms that are representative of the body of work. Chapter 3 continues with detailed descriptions and complexity analysis of the algorithms evaluated based on [3–6] and the proposed algorithm. Chapter 4 describes the method and metrics for the performance evaluation of the five DCPA algorithms and the results of this evaluation: a comparative performance study under a common set of assumptions and conditions. Chapter 5 is a sensitivity analysis of the remaining assumptions. Finally, the main conclusions, as well as ideas for the extension of this work, are presented in Chapter 6.

Chapter 2

System Model and Problem Formulation

2.1 System Model

This thesis considers a cognitive network of spectrum agile radios that seek to create a self-organized topology through frequency channel selection and power control. This system model defines two sets, a set of frequency channels $\mathcal{C}$ and a set of communications links $\mathcal{L}$. Each link $i \in \mathcal{L}$ comprises a transmitter and receiver, which seek to establish a wireless communications link using a channel $c \in \mathcal{C}$. Interference between links occurs when the links use the same channel, thereby causing transmissions to conflict.

Interference modeling in the channel assignment literature usually belongs to one of two types: protocol or Signal to Interference and Noise Ratio (SINR) model. The protocol model assumes that interference is a binary event, rather than a measurable state belonging to a continuum, as in the SINR model. In the protocol model, the transmitter of link i will assume a fixed communication and/or interference distance. The region over which the transmitter can communicate with a receiver is represented as a disk. In this disk, centered about the transmitter, link i communicates using channel c. Other receivers operating within this disk of link i cannot use channel c, since the receivers will experience an unacceptable level of interference. Thus, the problem is converted into a graph-coloring problem where each link is represented as a vertex, edges indicate potential interfering links, and colors represent channels. The graph coloring problem is solved when adjacent vertices are of different colors. While this does simplify the DCPA problem, coloring problems are NP-Complete, requiring graph-coloring heuristics [9].

Other works dismiss the protocol model as unrealistic since it does not consider aggregate interference, fading, path loss and power control of a real system [10, 11]. Many works, instead, use the SINR model [3–7, 9, 10]. However, dismissing the protocol model as unrealistic does add complexity. Power control is considered as well as path loss and fading. Selection of the appropriate transmitter power level involves tradeoffs. Increasing transmitter power increases the SINR of the receiver, but also introduces more co-channel interference, which could prevent other links from communicating. Despite the added complications, the SINR model is used for the baseline comparisons, but the protocol model also used to assess the impact of adopting a less realistic model of interference.

Given a set of communications links operating on a channel c, $\mathcal{L}_c$, the SINR of the receiver of link $i \in \mathcal{L}_c$, γ_i, is determined by:

$$\gamma_i = \frac{G_{i,i} P_i}{N_o + I_i}. \tag{2.1}$$

$G_{j,i}$ is the gain between the transmitter of link j and the receiver of link i. The variable P_i denotes the power of the transmitting node of link i, and N_o the thermal noise. I_i is the interference that the receiver link i experiences, expressed as:

$$I_i = \sum_{j \in \mathcal{L}_c, j \neq i} G_{j,i} P_j. \tag{2.2}$$

In this system model, this thesis defines a feasible link as a link whose receiver SINR is above a threshold β. This definition of a feasible link forms the basis for the optimization framework and metrics in this thesis. Prior work [2–5, 12] adopts the requirement that the receiver SINR of a link be above a specific threshold for the communication to be feasible. From feasible communication between links, other metrics are derived such as normalized throughput [5] and percentage of blocked calls [4]. Thus, a unifying comparison of different algorithms is best performed by focusing on the feasibility of communication links, as captured by the feasibility ratio metric described in Chapter 4.

2.2 Optimization Framework

Given a set of transmitter-receiver pairs and corresponding feasibility constraints, the DCPA problem is to allocate limited resources (i.e. channels and transmit power) to links to maximize the total number of feasible links, and for these links, to minimize the aggregate transmit power. Using this definition, this thesis develops a unifying optimization problem to describe the objective of the DCPA algorithms studied in this thesis.

Maximize:

$$M \sum_{i \in \mathcal{L}} \sum_{c \in \mathcal{C}} l_i^c - \sum_{i \in \mathcal{L}} P_i, \tag{2.3}$$

Subject to:

$$\sum_{c \in \mathcal{C}} l_i^c \leq 1 \qquad \forall i \in \mathcal{L}, \tag{2.4}$$

$$P_i \geq l_i^c \beta \left(\frac{N_o}{G_{i,i}} + \sum_{j \in \mathcal{L}, j \neq i} \frac{G_{j,i}}{G_{i,i}} P_j l_j^c \right) \quad \forall i \in \mathcal{L}, c \in \mathcal{C}, \tag{2.5}$$

$$0 \leq P_i \leq P_{\max} \quad \forall i \in \mathcal{L}. \tag{2.6}$$

The optimization variable l_i^c reflects the assignment of channel c to link i as described by:

$$l_i^c = \begin{cases} 1 & \text{if link } i \text{ is assigned channel } c \in \mathcal{C} \\ 0 & \text{otherwise.} \end{cases}$$

M is a weighting factor that, when sufficiently large, prioritizes maximizing the number of feasible links over minimizing the total transmit power in the network. The constraint expressed in inequality (2.4) restricts a link to only one channel. Since links are minimizing transmit power, inequality (2.5) allows the transmitter power to be set to zero if the link is not assigned a channel. Otherwise, the link is required to meet the minimum SINR requirement β. Inequality (2.6) constrains the maximum transmitter power to $P_{\max}$. [1]

2.3 Summary

In summary, the DCPA problem represents the task of assigning a set of channels $\mathcal{C}$ and transmit power to a set of links $\mathcal{L}$ with the objective of maximizing the number of feasible links and minimizing transmit power. The set of channels, $\mathcal{C}$, is a limited resource, which must be shared by all links. Links are feasible if and only if the SINR of link is above β. Therefore, algorithms addressing this problem must perform channel assignment in way to separate co-channel links to improve frequency reuse and minimize co-channel interference. Algorithms must also decide which transmitters should not operate in a channel-limited environment to maximize the objective function 2.3. These algorithmic mechanisms used to address the DCPA problem and specific algorithms selected for evaluation are discussed in Chapter 3.

[1] Collaboration was done with Umesh Shukla on developing the optimization framework.

Chapter 3

Algorithms

The DCPA problems have been the subject of wireless networks research for some time. Earlier channel assignment research studied cellular networks with the objective of increasing cell capacity by increasing spatial channel reuse of mobile devices [7, 8, 13–15]. Later DCPA work focused on enhancements to the IEEE 802.11 Medium Access Control (MAC) for similar purposes [9, 16, 17]. Other work focuses on the link layer effects of channel assignment, agnostic of network type [3–6]. Regardless of network model, DCPA algorithms in literature can be generalized into common channel assignment and power control techniques that are representative of the body of work. In this chapter, these representative channel and power assignment techniques are presented. The section closes by presenting the selection of algorithms used for evaluation, their descriptions, and our complexity analysis for each.

3.1 Channel Assignment Techniques from Literature

In channel assignment research, there are two frequently used distributed techniques: k-hop and Least Interfering Channel (LIC). In k-hop assignment, a common control channel is used for exchanging channel assignment information. Using the neighboring channel information, nodes determine channel availability. Given a node u, if none of k-hop neighbors of node u are using a channel c, channel c is available. The k-hop neighborhood is defined as any node within $d(u, v) \leq k$, where $d(u, v)$ is the least path distance (expressed in number of hops) between nodes u and v [9, 10, 17]. A similar approach uses Euclidean distances between nodes u and v [6]. The idea of this approach is to spatially separate co-channel transmitters to manage interference, opposed to examining each channel as in the LIC approach.

In LIC, channel assignment is performed by using the channel with the lowest measured interference [4, 7, 8, 18]. The motivation of using the LIC is so that the requisite SINR can be achieved by using a minimum amount of power and minimizing co-channel interference. This assignment can be performed by the receiver. However, other work assumes that the difference in the channel interference measurement between the receiver and the transmitter is negligible and the transmitter selects a channel for usage [18]. In some cases, LIC assignment requires that the channel with the lowest measured interference must be within some threshold I_{th} in order the channel to be a valid selection. The idea of this threshold is to prevent increasing co-channel interference on the network [8].

3.2 Power Control Techniques from Literature

Many works on power control work are based on one of two seminal papers by Zander and Foschini [14, 15]. These two works provide the basis for most of centralized and distributed power control techniques, respectively. In [14], Zander proved that there exists a maximum SINR, γ, for all links on channel c if and only if the maximum eigenvalue of $\mathbf{Z}$ is greater than one, where $\mathbf{Z}$ is defined as:

$$Z_{i,j} = \frac{G_{i,j}}{G_{i,i}}. \tag{3.1}$$

Furthermore, global knowledge of crosslink gains can be used to determine the optimum power levels of the links on channel c when (3.2) reaches equality:

$$\frac{1+\gamma}{\gamma}\mathbf{P} \geq \mathbf{ZP}, \tag{3.2}$$

where $\mathbf{P}$ is the column power vector of the links on channel c. This key result and analysis are leveraged by many centralized power control algorithms [3, 5, 19, 20].

A common approach used for distributed power control was first presented in [15]. In Foschini's iterative power control algorithm, transmitters iteratively adjust power such that the receivers are able to achieve an SINR above β according to equation (3.3)

$$P_i\,(k+1) = \frac{\beta}{\gamma}P_i(k), \tag{3.3}$$

where k represents the iteration number. In [15], Foschini proved that this simple decentralized power control algorithm executed by individual links exponentially converges to a power optimal solution for the set of links using channel c. This same technique has been leveraged or proposed in many other works [3, 6, 21, 22] to provide a distributed power control mechanism.

3.3 Algorithms

After a review of the DCPA literature on multi-channel ad hoc networks, we adapted algorithms based on the works of [3–6] for our comparative analysis. We adapted some of the underlying assumptions of each work to allow for equitable comparison, while maintaining their unique algorithmic features. In light of changes from their original work in [3–6], these adapted algorithms are renamed as: LICNPA, SCSIPA, LICIPA, MPIA, and CGA. We also propose a new distributed algorithm LICIPA, which combines mechanisms from [4, 6]. We selected these algorithms to illustrate the tradeoffs between different control modes (centralized versus distributed) and among assignment techniques as presented in each algorithm description. We also developed a complexity analysis for each of the five algorithms, presented with the algorithm descriptions.

3.3.1 Least Interfering Channel and Non-Iterative Power Assignment (LICNPA)

LICNPA uses LIC assignment and a distributed non-iterative power control similar to equation (3.5). In LICNPA, link i is assigned the channel that has the lowest measured interference at the receiver and below a threshold parameter, I_{th}. If no channel is below I_{th}, the link is infeasible. If a link is assigned a channel, the transmitter begins with initial power P_{ref}. If the SINR of the receiver is below β, the transmitter increases power in a one-step increment using the following equation:

$$P_i = \min\left(P_{\max}, P_{\text{ref}}\sqrt{\frac{I_{\text{th}}}{I_i}\frac{\beta}{\gamma_i}}\right). \tag{3.4}$$

I_i is the measured interference of the receiver of link i, as described in equation (2.2). If the SINR of the receiver of link i is still less than β after the power increase by equation (3.4), the link is considered infeasible. According to [4], the objective of equation (3.4) is to prevent subsequent admitted links from increasing interference such that the SINR of active co-channel links will drop below β. This power control scheme never reduces transmit power, making the overall system performance sensitive to P_{ref}. In LICNPA, links are admitted sequentially.

LICNPA selects the LIC, and co-channel links are minimally affected by the added interference of the new transmitter, thereby maximizing the number of feasible links. Additionally, by selecting the channel with the least amount of interference, less power is required for the SINR to remain above β, thus minimizing the transmit power of each link.

The derivation of the complexity of LICNPA is shown in Figure 3.1. LICNPA performs

Least Interfering Channel and Non-Iterative Power

$O(LC)$ $\begin{cases} O(L) \text{ For Each Link} \\ \quad O(C) \text{ LIC Assignment} \\ \quad O(1) \text{ Power Control} \\ \text{End Link} \end{cases}$

Figure 3.1: Complexity derivation for LICNPA

a two-step operation for every link, $O(L)$. First, it must determine the LIC for channel assignment, $O(C)$, and adjust power of the link, $O(1)$. This results in a complexity of $O(CL)$ for LICNPA.

3.3.2 Spatial Channel Separation and Iterative Power Assignment (SCSIPA)

Unlike the original proposal of [6], SCSIPA assumes frequency channels and distributed power control, as opposed to time slots and centralized power control. SCSIPA also assumes a common control channel in which nodes exchange location and channel assignment information with one another. Using the location and channel assignment information, the transmitter node of link i determines which receivers are within distance $d_{i,i}$, where $d_{i,i}$ is the Euclidean distance between the transmitter and receiver of link i. The transmitter of link i then randomly selects a channel c not being used by the neighboring receivers within distance $d_{i,i}$.

After the channel assignment for link i, the transmitter begins transmitting with initial power parameter P_{ref}. All transmitters on channel c then iteratively adjust their transmit power according to:

$$P_i\left(k+1\right) = \min\left(P_{\max}, \frac{\beta}{\gamma_i} P_i\left(k\right)\right), \tag{3.5}$$

where k is the iteration number. Foschini in [2] demonstrated that when transmitters use equation (3.5) to adjust their power levels, the transmit powers of the links will converge

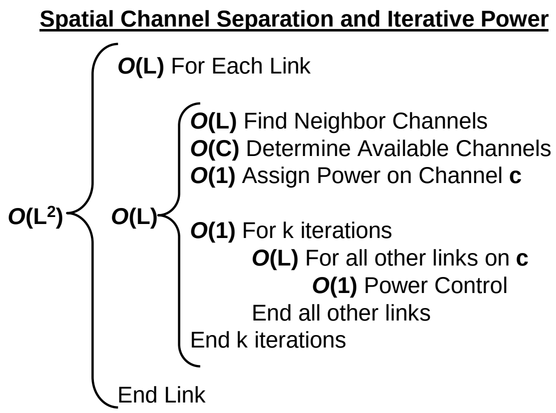

Figure 3.2: Complexity derivation for SCSIPA

exponentially. In SCSIPA, if the link cannot maintain an SINR of at least β without the transmit power of the link exceeding $P_{\max}$, the link is infeasible and the power of the link is set to zero. This procedure is performed sequentially for each link. This power assignment technique is unlike the centralized power control of [6] in which transmitter power levels are coordinated and assigned simultaneously.

SCSIPA manages interference among co-channel links by spatially separating interferers. Using equation (3.5), transmitter power is minimized. This reduction in power also reduces interference on co-channel links. In SCSIPA, channel and power assignment work in conjunction to maximize the number of feasible links and minimize power.

The derivation of the complexity of the SCSIPA is shown in Figure 3.2. SCSIPA performs channel assignment and power control for each link, $O(L)$. The link must discover the channel assignment of the $d_{i,i}$ neighbors by control messages from at most L links, $O(L)$. The link then determines and selects a channel not used by the $d_{i,i}$ neighbors, $O(C)$. After the initial power is assigned to a link, transmit power levels are allowed converge, for at most, L links, $O(L)$. Since we assume $L \gg C$, the dominant operation is determining neighbor channel information and allowing power levels to converge, both $O(L)$. Since this procedure is performed for every link, the complexity is $O(L^2)$ for this decentralized algorithm.

3.3.3 Least Interfering Channel and Iterative Power Assignment (LICIPA)

LICIPA is an algorithm created by combining power control from SCSIPA and channel assignment from LICNPA. In LICIPA, a link is assigned to the LIC as long as the received power of the LIC is below I_{th}. If no channel has received interference power below I_{th}, the link is infeasible. If a link is assigned a channel, the transmitter begins with initial power P_{ref}. After channel assignment, equation (3.5) is used by the links to perform power control and adjust power iteratively. If a link cannot maintain a SINR level of β without the transmit power of the link exceeding P_{max}, the link is infeasible and the power of the link is set to zero. In this algorithm, each link is admitted sequentially. LICIPA uses the LIC and the transmit power of equation 3.5 for maximizing the number of feasible links and minimizing transmit power.

Figure 3.3 shows the complexity derivation for LICIPA. The complexity for this algorithm is similarly derived as for SCSIPA and LICNPA. Determining and assigning the LIC is $O(C)$. Power control is then iterated for all other links on the channel, $O(L)$. Since it is assumed that $C < L$, $O(L)$ dominates in the inner loop and the algorithm has a complexity of $O(L^2)$. [1]

3.3.4 Minimum Power Increase Assignment (MPIA)

MPIA is a centralized algorithm based on the *Minimum Incremental Power Algorithm* from [5]. In MPIA, global knowledge of cross-link gains is used to determine channel and power assignments. Using Zander's result, MPIA determines the feasibility of adding a new link into set $\mathcal{L}_c$, and if the new link is feasible, calculates the change in aggregate power ΔP_c resulting from adding the new link into set $\mathcal{L}_c$. The feasibility test and calculation of ΔP_c

[1] Collaboration was done with Umesh Shukla on developing the complexity analysis of the algorithms and developing CGA.

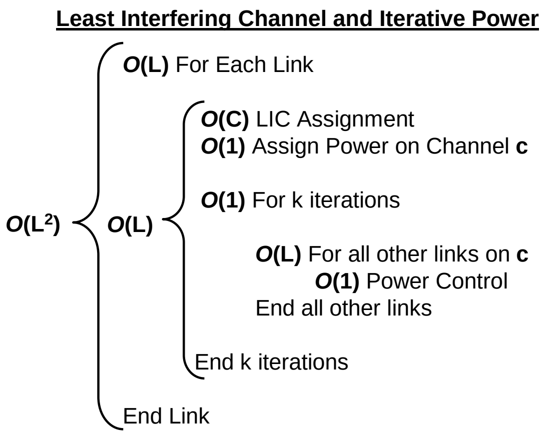

Figure 3.3: Complexity derivation for LICIPA

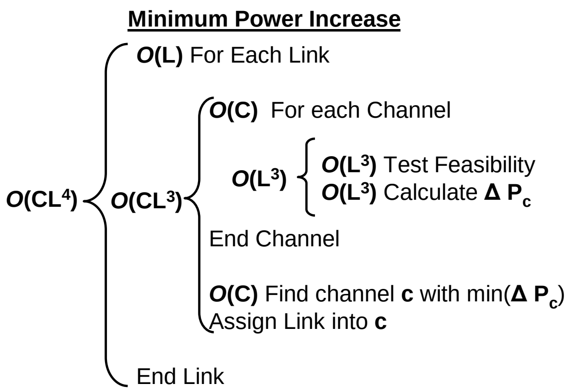

Figure 3.4: Complexity derivation for MPIA

are performed for all sets $\mathcal{L}_c$. MPIA then assigns the new link to the set $\mathcal{L}_c$ that yields the minimum ΔP_c. If the link cannot be assigned to any $\mathcal{L}_c$, then its transmit power is set to zero, and the link is declared infeasible. Unlike the original presentation of [5], MPIA requires all links to meet the same minimum SINR requirement, β. Additionally, the order of link admittance is selected randomly.

MPIA uses the objective function presented in (2.3). The algorithm first finds feasible assignments for each link, then selects an assignment with the minimum power increase. In other words, MPIA is a greedy assignment algorithm that seeks a feasible link assignment with a minimum power increase on $\mathcal{L}_c$.

The derivation of the complexity of MPIA is shown in Figure 3.4. Given $|\mathcal{L}| = L$ links and $|\mathcal{C}| = C$ communications channels, MPIA must test every link $O(L)$, in every channel, $O(C)$. Testing the feasibility of adding a new link to $\mathcal{L}_c$ requires calculating the eigenvalue of a matrix whose dimensions are, at most, $L \times L$. The dominant operation in the eigenvalue calculation is the determinant, which has a complexity of $O(L^3)$ [23]. ΔP_c requires calculating the inverse of a matrix whose dimensions are at most $L \times L$. By Gauss-Jordan elimination, the calculation of the matrix inverse has a complexity of $O(L^3)$ [23]. Both calculations for feasibility and ΔP_c are estimated for the worst case as $O(L^3)$. $O(L^3)$ dominates in the algorithm complexity, and combining the outer loops results in an algorithm complexity of $O(CL^4)$ for this centralized algorithm.

3.3.5 Conflict Graph Assignment (CGA)

[2] CGA, based on [3], maximizes the number of feasible links through a greedy assignment algorithm using global knowledge of the cross-link gains in a weighted conflict graph. The algorithm begins by calculating the number of possible feasible links for each unassigned channel by attempting to place all links on each unassigned channel. After this calculation, CGA assigns the channel that supports the maximum number of feasible links. Power control is done subsequently to minimize total power consumption.

To calculate the number of feasible links for each unassigned channel, an adjacency matrix of weighted edges of the conflict graph is represented by:

$$\mathbf{G}(i,j) = \begin{cases} G_{i,j} & \text{if i} \neq \text{j} \\ 0 & \text{if i=j.} \end{cases} \tag{3.6}$$

Using $\mathbf{G}$, CGA calculates the potential network interference introduced by the transmitter

[2] Collaboration was done with Umesh Shukla for the development of the CGA algorithm

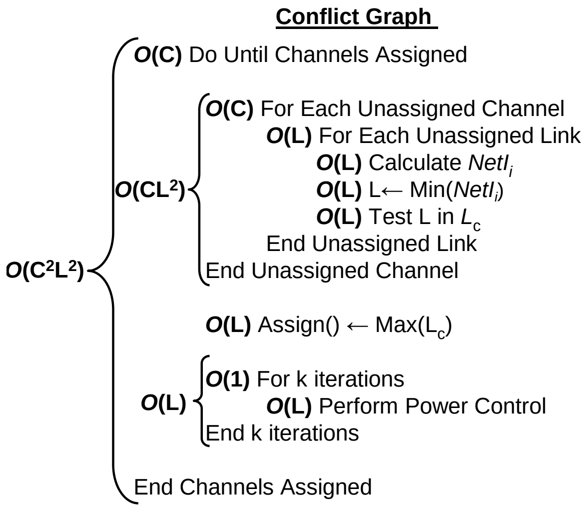

Figure 3.5: Complexity derivation for CGA

of link i as:

$$NetI_i = \sum_j G_{i,j}. \tag{3.7}$$

The link that has the $\min(NetI_i)$ is tested for feasibility in $\mathcal{L}_c$. To test feasibility, each γ_i is then calculated with $P_i = P_{max},\ in \in \mathcal{L}_c$. If the addition of the new link into $\mathcal{L}_c$ would not cause γ_i to drop below β for any $i \in \mathcal{L}_c$, the link can be added into set $\mathcal{L}_c$; otherwise, the link is not added. In either case, the link is discarded from $\mathbf{G}$, and $\mathbf{G}$ is recalculated to determine the next link with the $\min(NetI_i)$. The process is repeated until all links are attempted. The number of feasible links for each unassigned channel is calculated in the same manner. The channel which supports the maximum number of links, $\max|\mathcal{L}_c|$, is then assigned $\mathcal{L}_c$. This routine continues until all channels are assigned. If a link cannot be added into any channel, the link is infeasible.

While [3] does not use power control to minimize aggregate transmit power or reduce interference, it does suggest using the distributed power control mechanism in [2]. In CGA, upon completion of channel assignment, equation (3.5) is used to calculate the power of all links with initial power $P_i = P_{\max}$. Convergent power levels are then calculated for each link and assigned. In summary, CGA uses the objective function in (2.3) as a greedy assignment algorithm that seeks to maximize the number of feasible links and then minimize the total transmit power by equation (3.5).

The derivation of the complexity of CGA is shown in Figure 3.5. CGA assigns links to a channel in every iteration, $O(C)$. For every unassigned channel, $O(C)$, CGA, in the worst case, tests every link, $O(L)$. For all links, the network interference, the minimum interferer, and test for feasibility in $\mathcal{L}_c$ are calculated, each with complexity $O(L)$. Once the assignment for a particular channel is completed, $O(L)$, the power levels are calculated for all links in the channel, $O(L)$. The channel assignment operations executed for every link have a dominant complexity of $O(CL^2)$. Since this process is repeated until all channels are assigned, the worst-case complexity of CGA is $O(C^2L^2)$.

3.4 Summary

While there exists many different algorithms addressing power control there have been some basic re-occuring mechanisms which are commonly used. Algorithms commonly use either channel assignment by k-hop or LIC. The power control mechanisms developed by Zander and Foschini are also commonly used. Algorithms based on the works of [3–6] where developed to examine the trade offs between control modes and channel/power assignment mechanisms. These algorithms are named LICNPA, SCSIPA, LICIPA, MPIA, and CGA. LICNPA, SCSIPA, and LICIPA are distributed algorithms, while MPIA and CGA are centralized. Complexity for these algorithms as well as their channel and power assignment techniques are summarized in Table 3.1. In Chapter 4, we will show how the evaluation method and metrics are useful in characterizing algorithm performance.

Algorithm	Complexity	Channel Assignment	Power Assignment
LICNPA	$O(CL)$	Least Interfering Channel	$P_i = \min\left(P_{\max}, P_{\mathrm{ref}}\sqrt{\frac{I_{\mathrm{th}}}{I_i}\frac{\beta}{\gamma_i}}\right)$
SCSIPA	$O(L^2)$	Unused Neighbor Channel	$P_i\left(k+1\right) = \min\left(P_{\max}, \frac{\beta}{\gamma_i}P_i\left(k\right)\right)$
LICIPA	$O(L^2)$	Least Interfering Channel	$P_i\left(k+1\right) = \min\left(P_{\max}, \frac{\beta}{\gamma_i}P_i\left(k\right)\right)$
CGA	$O(C^2L^2)$	$\mathcal{L}_c$ with minimum interference	$P_i\left(k+1\right) = \min\left(P_{\max}, \frac{\beta}{\gamma_i}P_i\left(k\right)\right)$
MPIA	$O(CL^4)$	$\mathcal{L}_c$ with minimum power increase	$\frac{1+\gamma}{\gamma}\mathbf{P} \geq \mathbf{ZP}$

Table 3.1: Algorithm Summary

Chapter 4

Results

In this chapter, the evaluation method and metrics (feasibility ratio and average power per link) are introduced, followed by the results. The results are shown by comparing baseline surface plots for the algorithms using the feasibility ratio and average power per link. Comparative plots are used to establish relative performance among the algorithms. The chapter concludes by comparing the algorithm feasibility ratio and run time as a function of the number available channels.

4.1 Evaluation Method

The main goal of this work is to develop an evaluation method that can equitably compare distinct DCPA algorithms. To perform this comparison, the algorithms are given a set of L potential links in which they seek to fulfill the objective function defined in equation (2.3). We consider links that have a maximum separation distance between the transmitter and receiver of $d_{\max}$. Performance metrics are evaluated by varying the density of links, $d_{\max}$, and then number of channels.

We evaluate algorithm performance by varying link density because we seek to understand how well each algorithm is able to manage interference through channel assignment and power control. By increasing link density, we increase the aggregate interference experienced by each link. When density is low, the mean distance among potential interferers is larger than the intended transmitter-receiver distance. As the density increases, the distance between a transmitter and its intended receiver will approach the mean distance among potential interferers. Therefore, increasing the density provides a means to increase aggregate interference for each link.

Additionally, the choice of $d_{\max}$ plays a role in SINR being dominated by either noise or interference. If $d_{\max}$ is small, the SINR of each link will be dominated by noise. Conversely, if $d_{\max}$ is large, the SINR of each link will be dominated by interference. Additionally, if $d_{\max}$ is sufficiently large and the density sufficiently low, links could be infeasible because of attenuation from path loss. Therefore, examining different values of $d_{\max}$ while varying the link density are important for this evaluation to explore these regions of interest. The four regions of noise dominant, transition, interference dominant and path loss provide the basis for discussion of results.

4.2 Metrics

For algorithm evaluation, this thesis chooses two metrics that are directly related to the objective function: feasibility ratio and average power per link. The feasibility ratio, κ, is the ratio of the number of feasible links $|\mathcal{L}_f|$ to the number of potential links $|\mathcal{L}|$:

$$\kappa = \frac{|\mathcal{L}_f|}{|\mathcal{L}|}. \tag{4.1}$$

We use the feasibility ratio as a normalized measure of algorithm performance.

Mobile nodes have a limited battery life and therefore, power consumption is a concern for network longevity [24]. The average power per link, χ, is expressed as:

$$\chi = \frac{\sum_{i \in \mathcal{L}_f} P_i}{|\mathcal{L}_f|}. \tag{4.2}$$

4.3 Simulation Environment

L links are randomly placed in a square simulation area under the constraint $d_{i,i} \leq d_{\max}$. C frequency channels are fixed, and each of the five algorithms discussed in Chapter 3 is executed to solve the DCPA problem. New topologies are generated and the algorithms are executed again until 1,000 trials are completed. Upon completion, metrics are collected and the simulation area is reduced. New trials are then executed in a smaller simulation area. For each of value $d_{\max}$, the simulations begin with a minimum density $D_{\min}$ and end with a maximum density $D_{\max}$. The experiments are then repeated for the new value of $d_{\max}$. In the simulation, we use baseline parameter values of β=10dB, N_o=$-$110dBm, $P_{\max}$=30dBm, $\alpha = 4$, and L=100 links.

4.4 Baseline Surface Plots

Baseline simulations for this study first seek to examine the noise and interference dominant regions by varying $d_{\max}$ and link density. In these plots, a path loss exponent was assumed $\alpha = 4$, $L = 100$, $C = 40$, and independent Rayleigh fading on all channels. These results are presented by first introducing a representative surface plot for each metric (see Figures 4.1 and 4.2). Different operating regions are labeled in these surface plots. The surface plot for feasibility ratio is introduced first, followed by the average power per link.

In the surface plots of Figure 4.1, four regions of interest are identified: noise dominant, interference dominant, transition, and path loss. The upper plateau of the surface is labeled the noise dominant region. In this noise dominant region, shorter link lengths minimize the effects of co-channel interference and produce a high feasibility ratio. The lower plateau is labeled interference dominant region. In the interference dominant region, the feasibility ratio remains constant because the average distance between interferers is the same as the average distance between transmitter receiver pairs. In other words, $d_{\max}$ has exceeded the diagonal of the square simulation area. Therefore, the $d_{\max}$ constraint is satisfied anywhere transmitter and receivers are placed. The slope between the upper and lower plateaus is labeled as the transition region in the surface. The slope below the interference dominant region is label path loss region, here the feasibility ratio decreases when $d_{\max}$ is large and density is low, causing links to be lost because of the attenuation from the separation distance. Comparative surface plots for feasibility ratio are shown in two-dimensional plots provided in Figure 4.3 for all algorithms.

Figure 4.4 shows the corroborating average power per link plot to Figure 4.3; regions are labeled similarly. The noise dominant region is characterized by decreasing average power per link because of shorter link lengths and lower densities. The interference dominant region corresponds to the lower plateau of the surface, and the transition region corresponds to the slope between the noise and interference dominant regions. Path loss is shown as the upper plateau of the surface. In the path loss region, links require higher transmit power to establish requisite SINR levels for communication because of the larger separation distance between transmitter and receiver pairs. Comparative surface plots for average power per link are shown in Figure 4.3 for all algorithms.

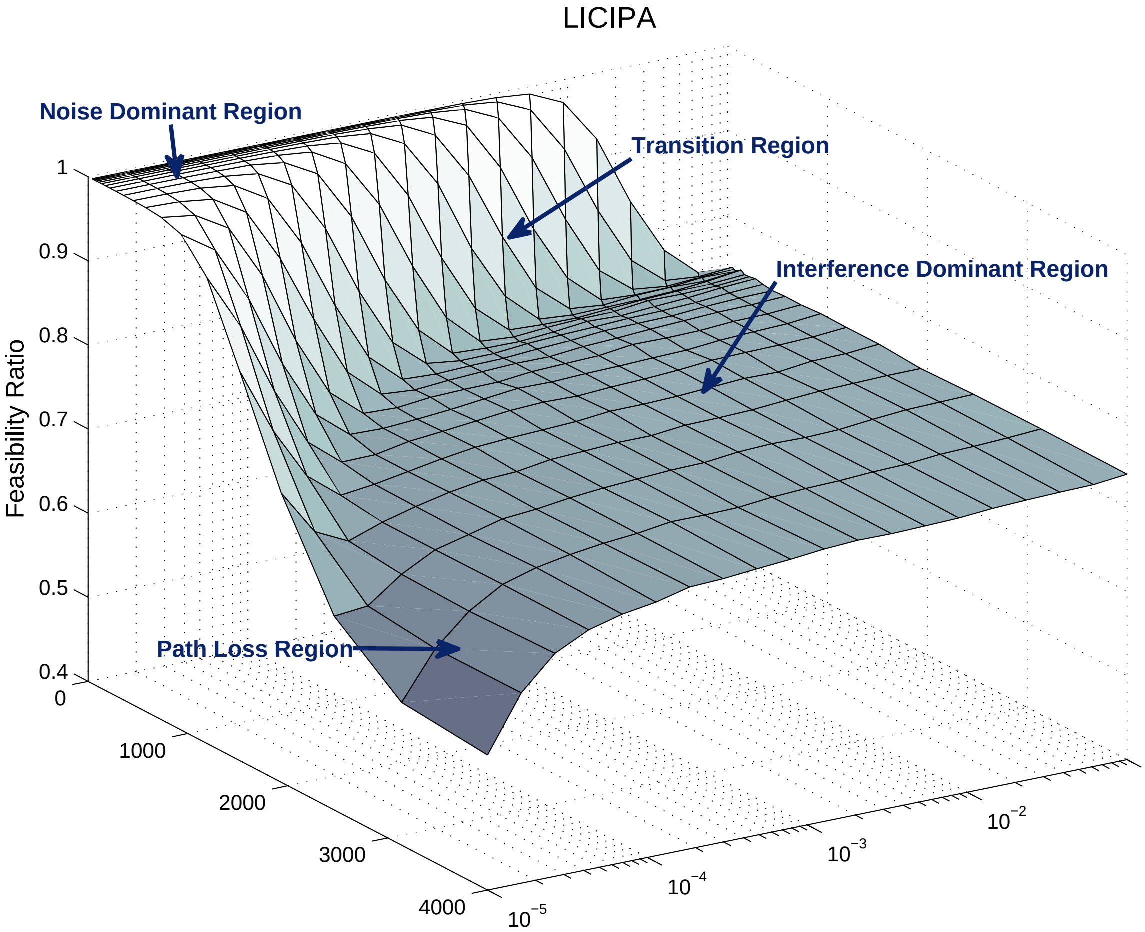

Figure 4.1: Baseline simulation results for LICIPA with L=100, C=40.

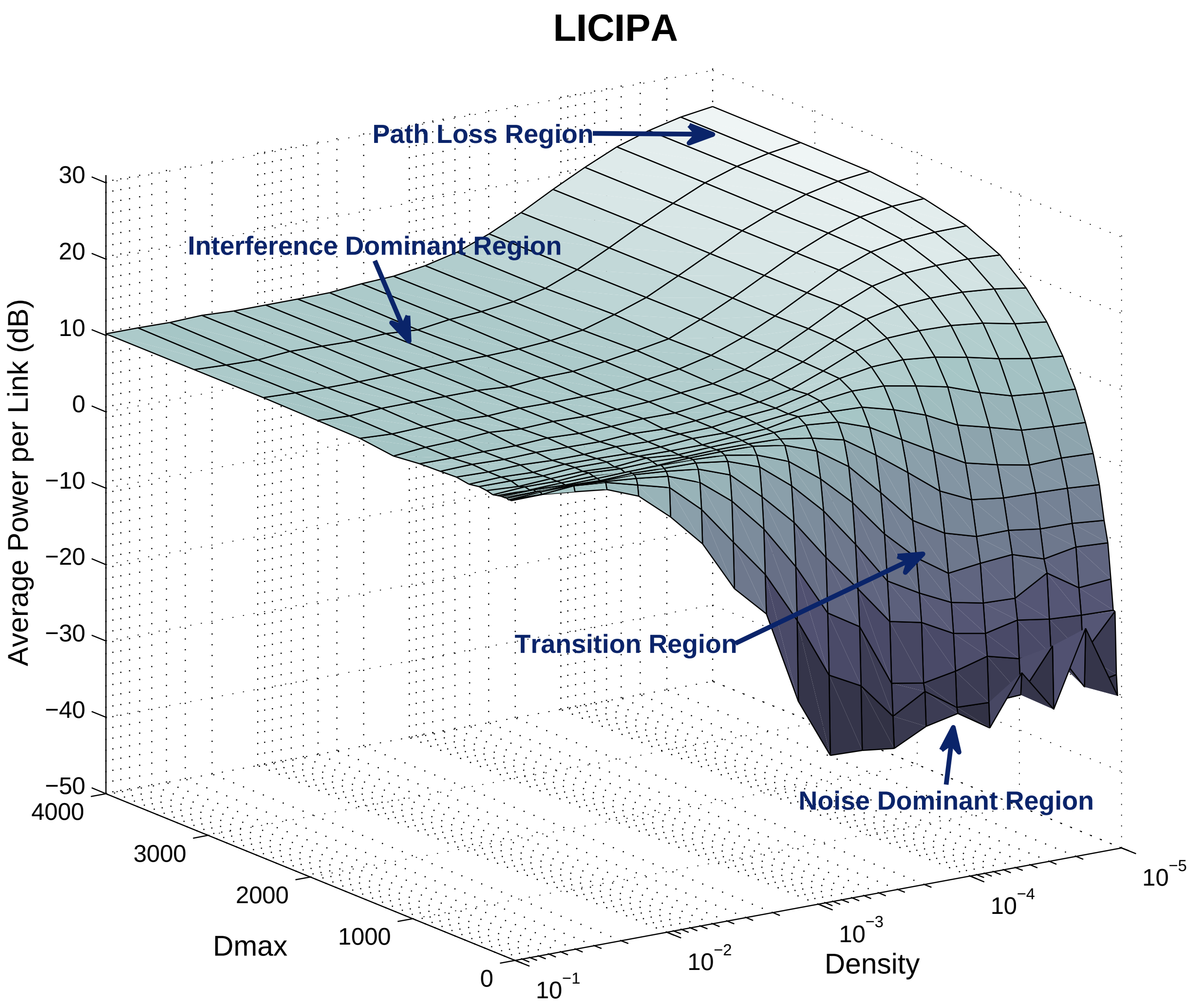

Figure 4.2: Baseline simulation results for LICIPA L=100, C=40

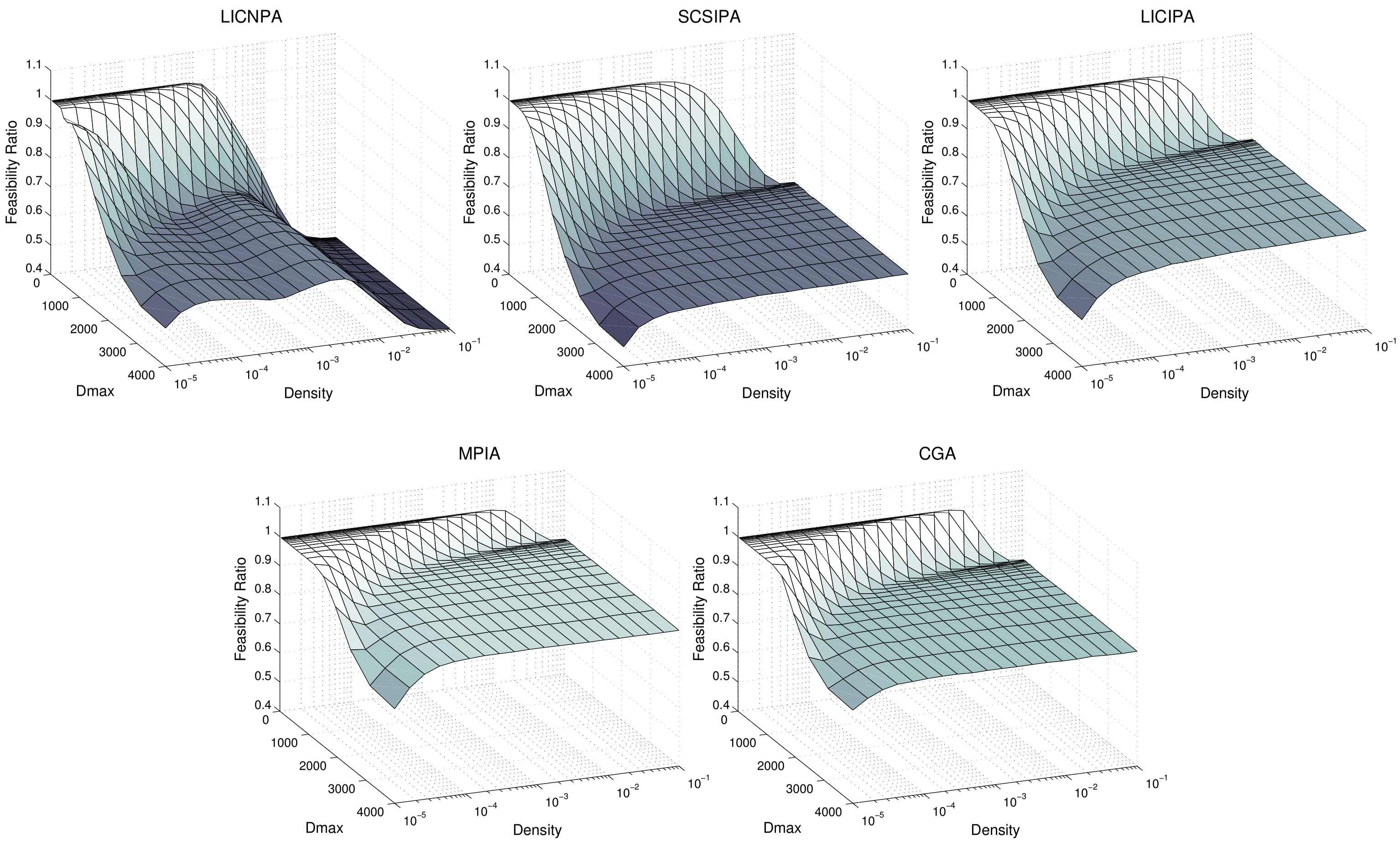

Figure 4.3: Baseline simulation feasibility ratio comparison with L=100, C=40

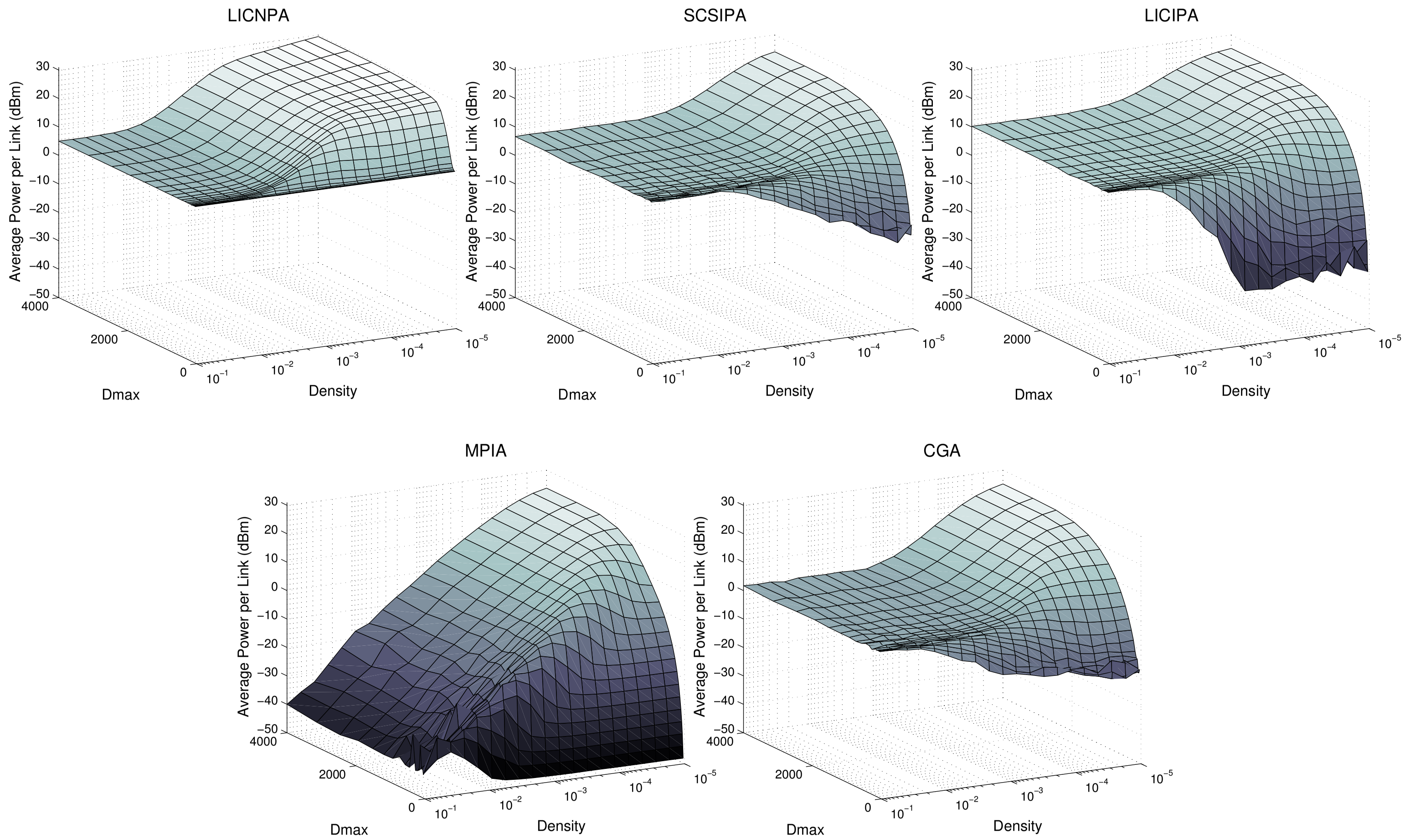

Figure 4.4: Baseline simulation average power per link comparison with L=100, C=40

4.5 Algorithm Comparison

Our results show that the algorithms exhibit distinct regions of operation based on link density and the value $d_{\max}$. To examine comparisons Figure 4.5 shows the performance of the feasibility ratio and average power per link for $d_{\max}$=350 (top plots) and $d_{\max}$=4000 (bottom plots), for all algorithms. In Figure 4.5, the four regions of interest are labeled: noise dominant, transition, interference dominant, and path loss. The 90% confidence interval for the feasibility ratio is approximately ± 0.003 (left plots) and $\pm 2dBm$ for average power per link (right plots).

The feasibility ratio plot with $d_{\max}$=350 (top left), identifies the noise dominant region as the region where the feasibility ratio is 1 for the algorithms. In this noise dominant region, shorter link lengths, relative to the simulation area, minimize the effects of co-channel interference and produce a high feasibility ratio. Increasing link density moves algorithm performance into the transition region between the noise and interference dominant regions. In Figure 4.5 (bottom left), the feasibility ratio declines when transitioning from the interference dominant region to the path loss region, because link density is low and $d_{\max}$ is large.

The average power per link plots provide corroborating data with the feasibility ratio plots. In the average power per link plot for $d_{\max}$=350 (Figure 4.5, top right), as density increases, the average power per link initially rises and then slightly decreases or remains constant. In the noise dominant region, the SINR is minimally affected by co-channel links, allowing for slightly lower transmit power before the peak. However, as the density increases and the effects of co-channel interference become greater, links must compensate for this by increasing power. This power increase corresponds to the initial rise in power we see in Figure 4.5 (top right). As the simulation transitions into the interference dominant region, the potential effects of co-channel interference reach their maximum. As density increases in the interference dominant region, algorithms show a slight decrease in transmit power because of the shorter link distances. Additionally, in the path loss region in Figure 4.5 (bottom right) we see much higher power per link because of increased link lengths.

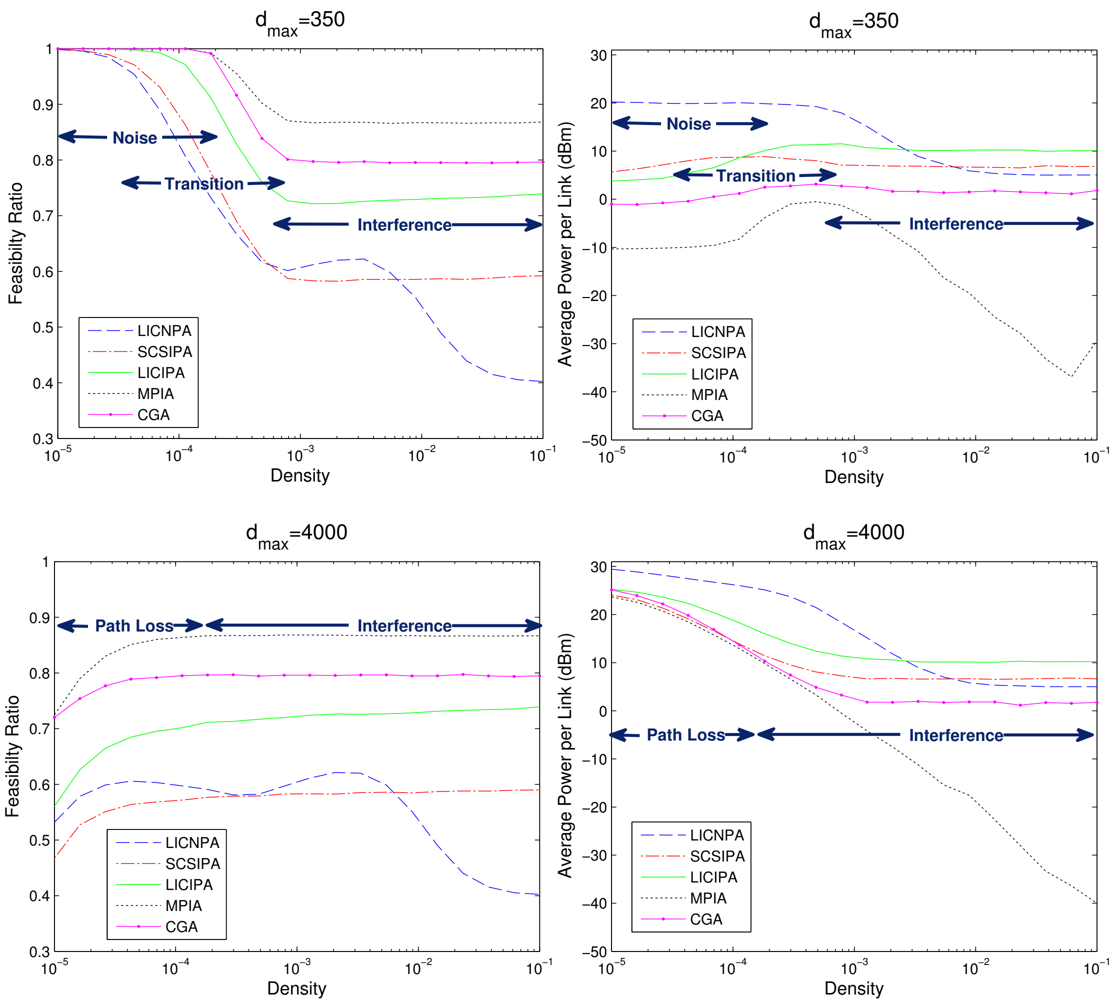

Figure 4.5: Baseline metrics algorithm comparison with L=100, C=40 with $d_{\max}$=350 and $d_{\max}$=4000. Plots with $d_{\max}$=350 show transition between noise dominant and interference dominant region. Plots with $d_{\max}$=4000 show transition between path loss and interference dominant region.

The results for LICNPA show distinct characteristics when compared to the other algorithms. These characteristics, most pronounced in the interference dominant region, are caused by the power control mechanism employed by the algorithm. LICNPA uses the quantity $\frac{I_{\text{th}}}{I_i}$ to adjust transmit power, which tends to increase transmitter power and co-channel interference excessively. As a result, LICNPA has the lowest feasibility ratio in the noise dominant and transition regions (Figure 4.5, top left). In the interference dominant region, the quantity $\frac{I_{\text{th}}}{I_i}$ will be closer to one, thus there is a reduction in relative transmit power and an increase in feasibility ratio. This corresponds to the reduced power per link in Figure 4.5 (top right) and the hump in the feasibility ratio in Figure 4.5 (top left) around $10^{-3} links/m^2$. As the density increases, LICNPA can only support as many available links as it has channels, since transmit power never reduces from its initial power of $P_{ref} = 5\ dBm$. The average power per link for LICNPA converges to 5 dBm in Figure 4.5 (top right). In summary, the power control mechanism used by LICNPA can cause undesirable effects in link feasibility because of unnecessary transmit power.

In terms of relative algorithm performance, MPIA achieves the best feasibility ratio performance and the overall lowest average power per link. While MPIA appears to have all the desirable features of a DCPA algorithm, it also has a unique disadvantage. In MPIA, the inverse of the cross-link gain matrix is used to calculate ΔP_c. In some cases, this matrix is close to singular, resulting in an incorrect transmit power assignment. These near singular matrices occur when the link gain is much greater than the gain from co-channel interfering links, $G_{i,i} \gg G_{j,i}$. An example of the effects of this matrix approaching singularity can be seen by the "kink" shown in the Figure 4.5 (top right). This "kink" is a result of incorrect power assignment, thus creating a wider confidence interval for average power per link.

Figure 4.6 shows, at a fixed density of 10^{-1} $links/m^2$ and $d_{\max}$=350, the feasibility ratio achieved by each algorithm as a function of the number of channels. In Figure 4.6, performance differences are small for $C < 20$. For instance, LICIPA (a distributed algorithm) has almost identical performance as CGA (a centralized algorithm). When $C > 20$, algorithms show larger differences in feasibility ratio. In addition, in some of the curves, the addition of more channels does not produce a linear improvement in feasibility ratio. When the algorithms have a sufficient number of channels, we see that all, except for SCSIPA, reach a feasibility ratio of 1.

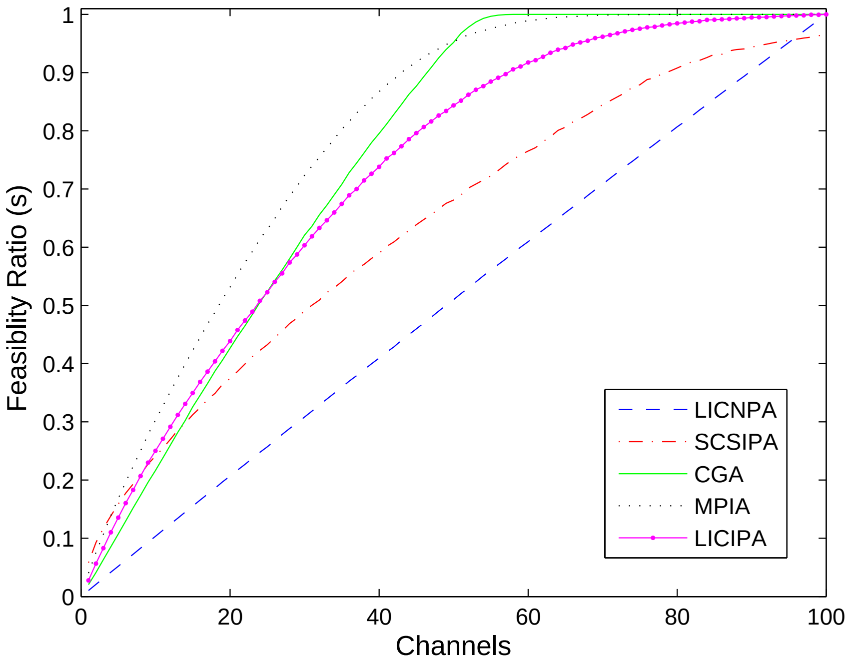

Figure 4.6: Feasibility ratio as a function of C, with $L = 100$, and fixed density 10^{-1} $links/m^2$.

We believe that SCSIPA does not reach a feasibility ratio of 1 because of channel assignment by spatial separation. In the case where $C = 100$, ideally, every link should have its own channel; however, links in SCSIPA select a channel that is not being used by the $d_{i,i}$ neighbors. Therefore, multiple links could select the same channel. If multiple links select the same channel, existing links could drop or admitting links could be infeasible, lowering the feasibility ratio.

In addition to the complexity derivations in Chapter 3, we also compare the algorithms according to average run time. Average algorithm run time metrics are shown in Figure 4.7 for a link density of 10^{-1} $links/m^2$, as a function of the number of channels. Three differences from our complexity analysis are apparent from Figure 4.7. First, we would expect MPIA to have the highest run time because its complexity is estimated as $O(CL^4)$. However, in general, the matrix used to test the feasibility and calculate ΔP_c has smaller dimensions than $L \times L$. Therefore, the complexity analysis is overly pessimistic when compared to the average.

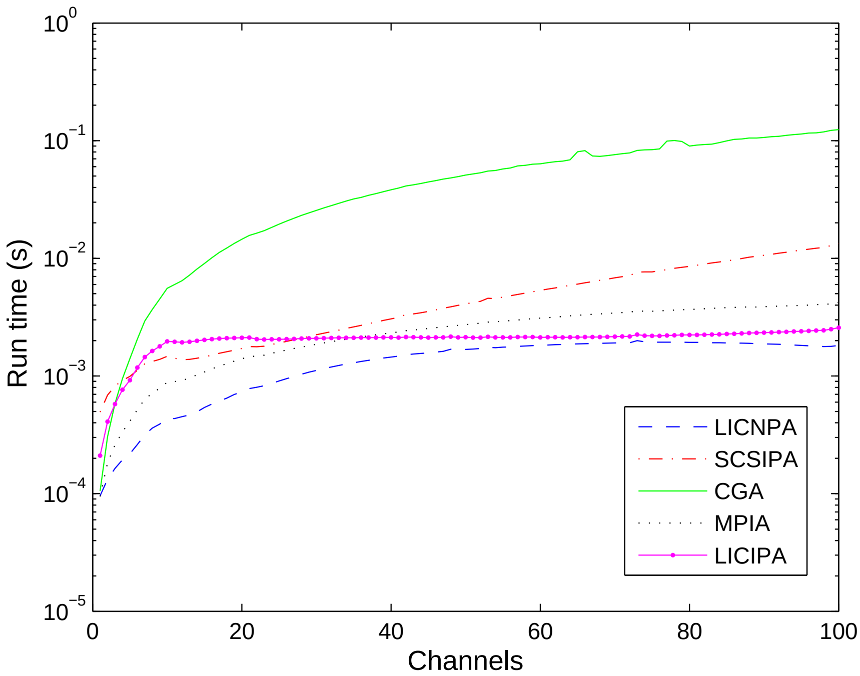

Figure 4.7: Average run time shown as a function of C.

4.6 Summary

Our results show that feasibility performance and average power per link is affected by the link density and the choice of d_{max}. The surface plots show that feasibility ratio and average power per link performance have four regions of interest: noise dominant, interference dominant, transition, and path loss. The interference dominant region occurs when the average distance between interferers is the same as the average distance between transmitter receiver pairs or $d_{\max}$ has exceeded the diagonal of the square simulation area. Algorithm comparisons of the feasibility ratio and average power per link for $d_{\max}$=350 and $d_{\max}$=4000 where shown. MPIA was the best performing centralized algorithm and LICIPA was the best performing distributed algorithm. LICNPA results were different from the other algorithms because of the power control mechanism that it employs. With fewer channels, algorithm performance is comparable. Average runtime as a function of the number of channels also was shown. In Chapter 5, we present our sensitivity results for the remaining simulation parameters and channel model assumptions.

Chapter 5

Sensitivity Analysis

This chapter presents a sensitivity analysis of the simulation parameters and channel model assumptions used in this thesis. This chapter has two goals. First, we examine how the number of links and channels can affect the feasibility ratio. Second, we examine how channel model assumptions affect the feasibility ratio. For the channel model, the path loss exponent, fading, and interference model were altered to understand what effects on performance would occur. The results are analyzed by examining relative and comparative performance effects of changing the simulation parameters and channel model assumptions.

5.1 Links and Channels

In this section, we evaluate the performance metrics of the DCPA algorithms by varying the number of links and channels in the interference dominant region. Figure 5.1 shows the results of this analysis in the interference dominant region with a density 10^{-1} $links/m^2$ and $d_{\max}$=4000 for all algorithms.

All plots show that as the number of links, and proportional number of channels, increases there is a slight increase in the feasibility ratio. As shown in Figure 5.1, the performance difference between 275 links and 300 links is small. This asymptotic limit is caused by the fixed link density of the experiment. Since the link density is fixed, as the number of links increases, the area also increases. Thus, the interference contribution from additional nodes becomes sufficiently small because of the larger simulation area. This results in an asymptotic limit for the feasibility ratio.

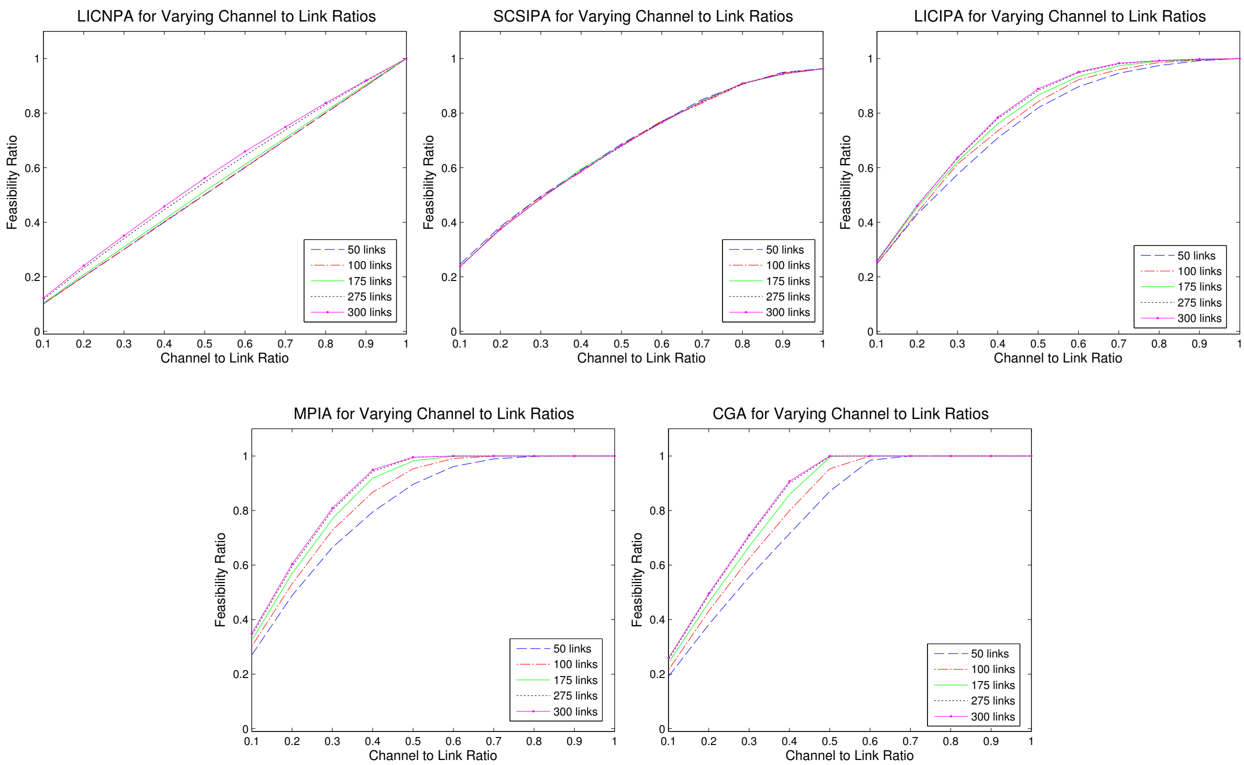

Figure 5.1: Number of links and proportional number of channels sensitivity results using a density of 10^{-1} $links/m^2$ and $d_{\max}$=4000.

5.2 Channel Model

To examine the effects of changing the channel model, we examined variations in the path loss exponent, fading, and interference model. The path loss exponent, α, was varied using values of $\alpha = 2$, $\alpha = 3$, and $\alpha = 4$. Additionally, a channel model with no Rayleigh fading and a path loss exponent $\alpha = 4$ was used. Finally, we also implemented an induced protocol model by allowing any receiver within the distance $d_{i,i}$ to be infinitely close and receivers outside the distance $d_{i,i}$ to be infinitely far away from the transmitter of link i. The effects of the changing channel model are shown for each algorithm in Figures 5.2, 5.3, 5.4, 5.5, and 5.6 for algorithms LICNPA, SCSIPA, LICIPA, MPIA, and CGA respectively.

As in previous algorithm comparisons, LICNPA has a different reaction to the changes in path loss exponent α than the other algorithms. This can be explained by the power control mechanism that the algorithm uses. As before, LICNPA uses the quantity $\frac{I_{\text{th}}}{I_i}$ to adjust transmit power, which tends to excessively increase transmitter power and co-channel interference. With different values of α, the interference experienced by each receiver is different and the corresponding power adjustment causes the usual behavior in the surface plots.

All other algorithms show a slight rise in the interference dominant region and the emergence of the distinct path loss region with increasing α. Increasing α from 2 to 4 decreases co-channel interference but also increases path loss between transmitter receiver pairs, thus creating the path loss region. When no Rayleigh fading is present, there is an increase in feasibility ratio because Rayleigh fading reduces co-channel interference. Additionally, we also see that the induced protocol model produces an increased feasibility ratio for all algorithms. For MPIA, the induced protocol model was not used because of the close to singular matrices discussed in the previous chapter.

Comparative plots for the changing parameters in the channel model are shown in Figure 5.7. Without considering LICNPA, relative performance order remains constant, except in the case of no Rayleigh fading. In the no fading plot of Figure 5.7 (bottom left), the performance of LICIPA is close to that of MPIA. In another observation, the performance of LICNPA is significantly improved with higher link densities because the induced protocol model does not consider aggregate interference in these cases.

5.3 Summary

Results from the link and channel sensitivity analysis show that at a constant density, feasibility performance approaches an asymptotic limit when the number of links increases. Results from this sensitivity analysis show that variation in α does not significantly change the performance order for most of the algorithms. The exception is LICNPA, whose performance is drastically affected since it uses the quantity $\frac{I_{\text{th}}}{I_i}$ to adjust transmit power. Overall, relative performance of the algorithms remains consistent when changing the parameters of the channel model.

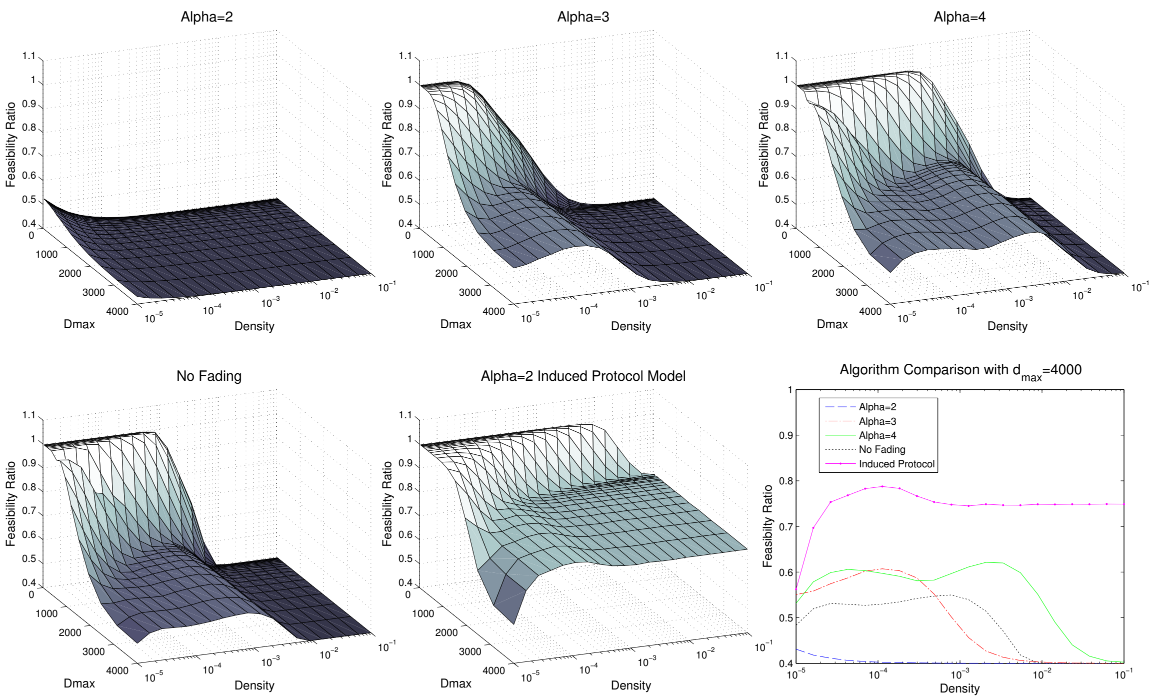

Figure 5.2: Sensitivity results for LICNPA. The power control mechanism used by LICNPA makes it sensitive to changes in α.

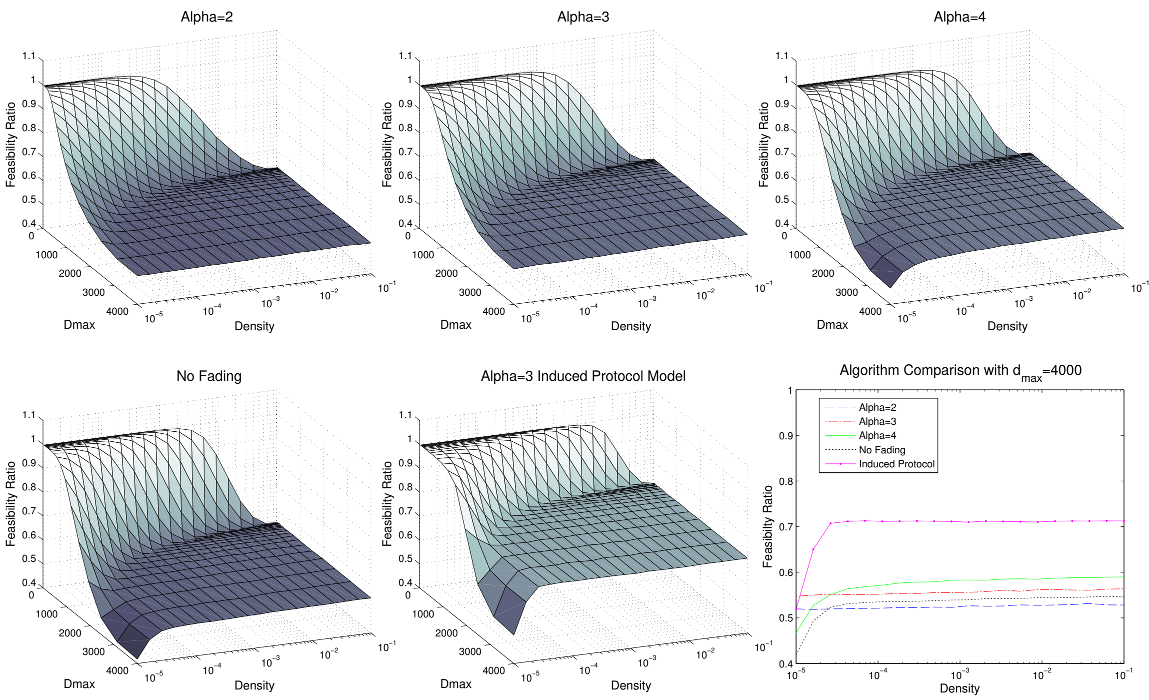

Figure 5.3: Sensitivity results for SCSIPA.

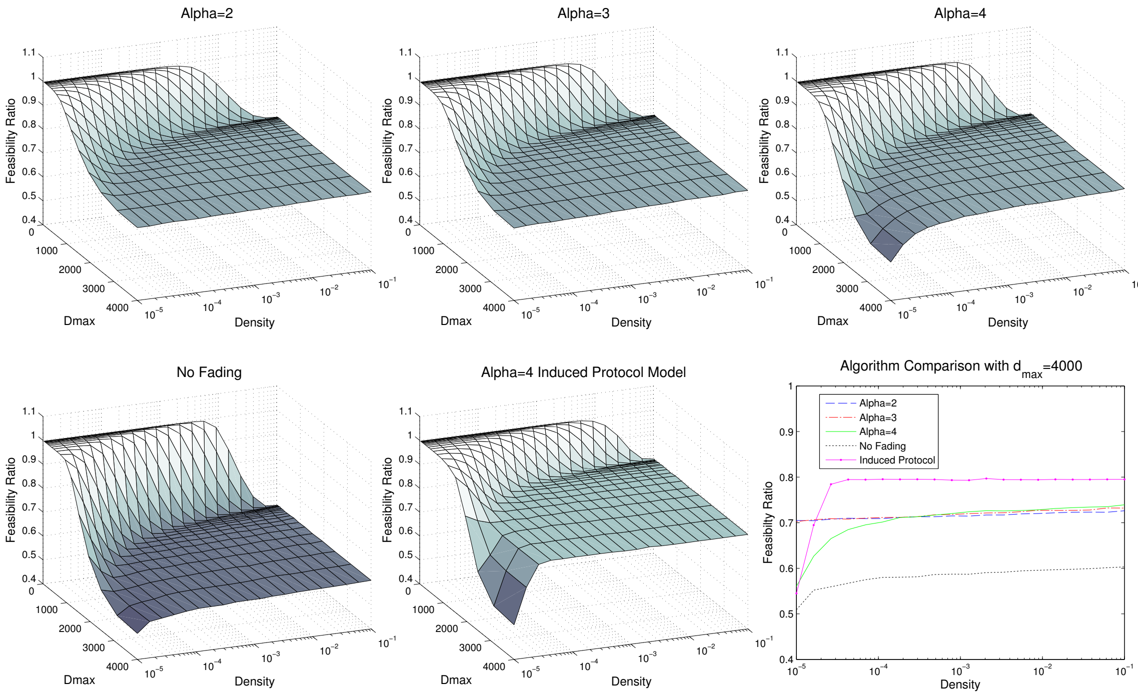

Figure 5.4: Sensitivity results for LICIPA.

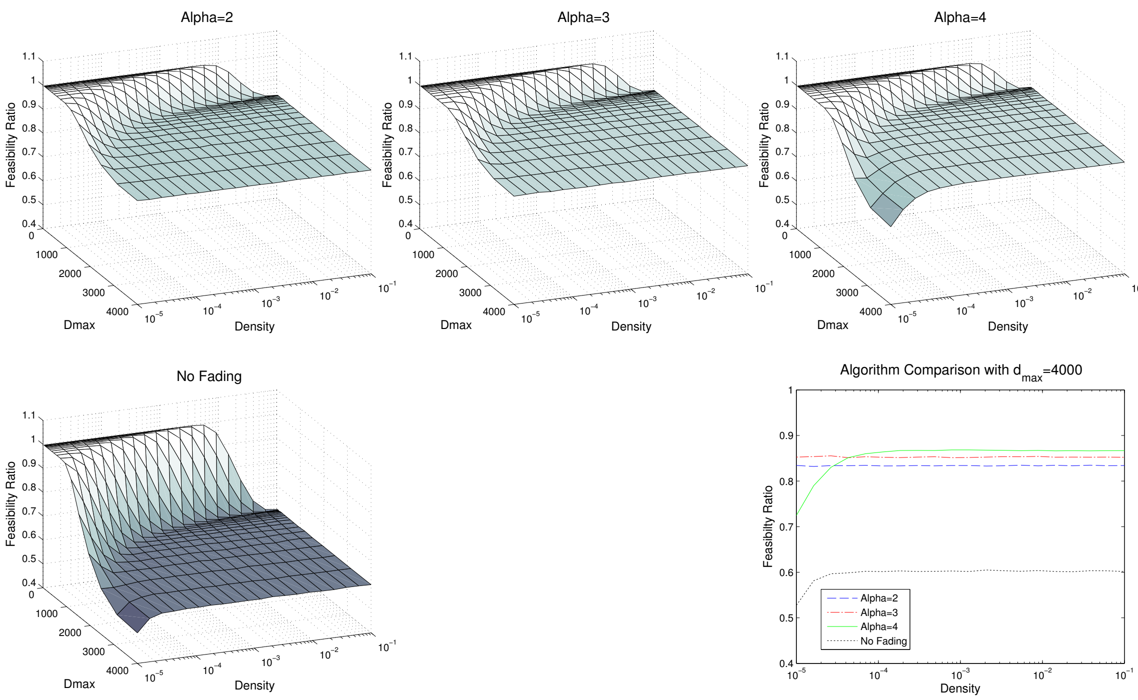

Figure 5.5: Sensitivity results for MPIA.

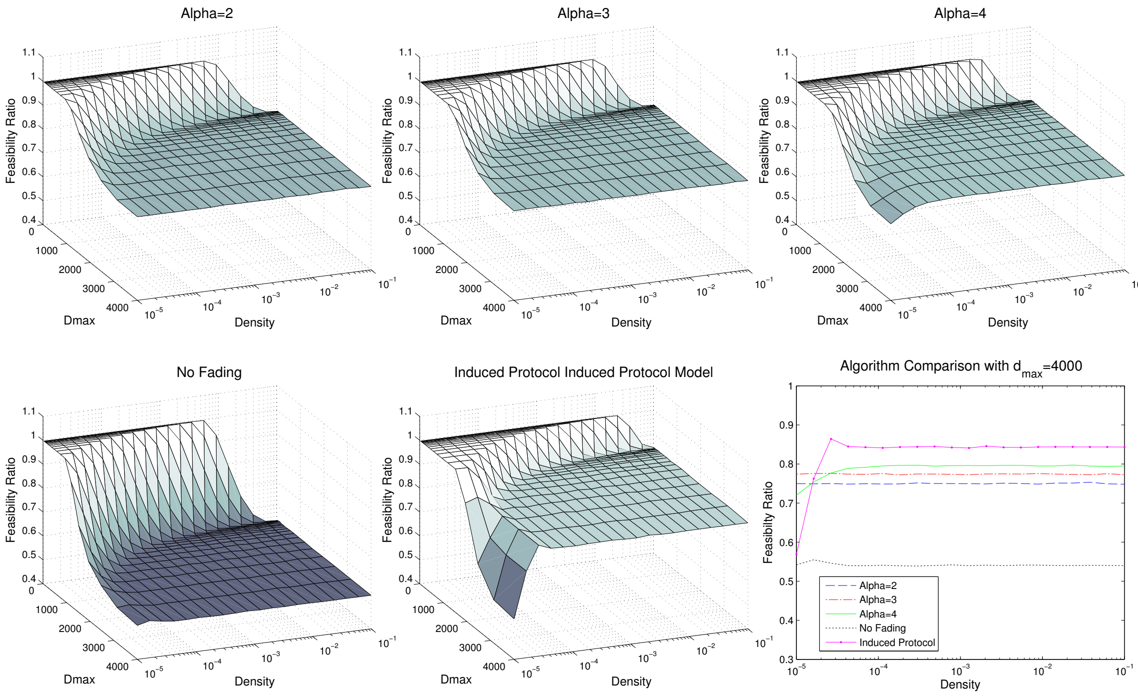

Figure 5.6: Sensitivity results for CGA.

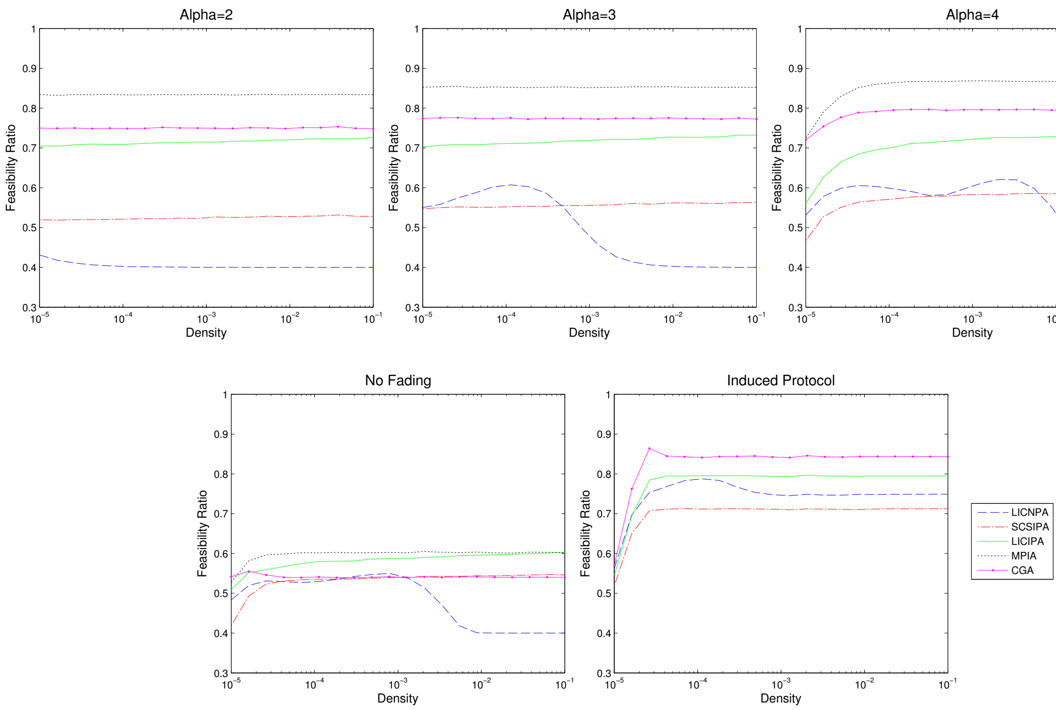

Figure 5.7: Comparative results from sensitivity experiments with $d_{\max}$=4000..

Chapter 6

Conclusion

6.1 Summary of Results

Our results demonstrate that for most of the channel assignment algorithms analyzed, the feasibility ratio is constant when in the interference dominant region. Additionally, we showed that comparative performance is a function of the number of channels and the link density. With few channels, the performance of all algorithms is comparable. Therefore, when considering network implementation with limited channel resources, the algorithm with the lowest complexity or run time should be selected.

The centralized algorithm MPIA has the overall best feasibility ratio and the lowest average power per link. Through assignment by the least change in transmit power, MPIA minimizes interference and increases the number of feasible links. However, implementation of this assignment faces the problem of inverting near singular matrices. CGA showed comparable performance, with the disadvantage of a significantly longer run time. Additionally, in the case of the centralized algorithms, the requirement of knowledge of cross-link gains for any algorithm is problematic in the implementation of a real system. As a distributed alternative, LICIPA is a reasonable option.

LICIPA does not require cross-link gain information and exhibits the overall lowest run time, complexity, and the overall best feasibility ratio among the distributed algorithms. As a comparison, when CGA and MPIA reaches a feasibility ratio of 1 at $C \approx 60$, LICIPA has a feasibility ratio of ≈ 0.9 (Figure 4.6). However, this does come at a cost of slightly higher average power per link. Compared to SCSIPA, LICIPA does not require location and channel information for assignment. Instead, it measures received power on all channels and selects the LIC. In terms of power iterations, LICIPA will cause fewer perturbations in overall network power than SCSIPA, because LICIPA uses the LIC. However, measuring received power on all channels does come at some computational cost, whereas selecting a channel based on control messages may incur less computational cost but generate more network overhead.

6.2 Open Issues

While channel assignment has been a widely explored field, we believe some open issues remain. First, how should a network dynamically adapt based on changing conditions due to spectrum availability and desired quality of service? We believe dynamically adaptations are important when considering the case of primary and secondary spectrum users. Second, how can a network maintain an optimal global topology through channel assignment when nodes only have access to local information? While some work has been done in combining aspects of routing and channel assignment, we believe there is still opportunity for contribution in this area. Finally, what learning and self-organization techniques could a CN use to improve network performance and what would be the tradeoffs? Overall, we believe that the analysis of channel assignment is an important first step in understanding how to create cognitive dynamic spectrum access network.

CGA Conflict Graph Assignment

CN Cognitive Network

DCPA Dynamic Channel and Power Assignment

DSA Dynamic Spectrum Access

LIC Least Interfering Channel

LICNPA Least Interfering Channel and Non-Iterative Power Assignment

LICIPA Least Interfering Channel and Iterative Power Assignment

MAC Medium Access Control

MPIA Minimum Power Increase Assignment

SCSIPA Spatial Channel Separation and Iterative Power Assignment

SINR Signal to Interference and Noise Ratio

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