Design of High Throughput Wireless Mesh Networks

by

Skanda N. Muthaiah

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Wireless Mesh Networks are increasingly becoming popular as low cost alternatives to wired networks for providing broadband access to users (the last mile connectivity). A key challenge in deploying wireless mesh networks is designing networks with sufficient capacity to meet user demands. Accordingly, researchers have explored various schemes in an effort to build high throughput mesh networks. One of the key technologies that is often employed by researchers to build high throughput wireless mesh networks (WMN) is equipping nodes with smart antennas. By exploiting the advantages of reduced interference and longer transmission paths, smart antennas have been shown to significantly increase network throughput in WMN. However, there is a need to identify and establish an upper-bound on the maximum throughput that is achievable by using smart antennas equipped WMN. Such a bound on throughput is important for several reasons, the most important of which is identifying the services that can be supported by these technologies. This thesis begins with a focus on establishing this bound.

Clearly, it is evident that smart-antennas cannot increase network throughput beyond a certain limit for various reasons including the limitations imposed by existing smart antenna technology itself. However with the spiralling demand for broadband access, schemes must be explored that can increase network throughput beyond the limit imposed by smart antennas. An interesting and robust method to achieve this increased throughput is by enabling multiple gateways within the network. Since, the position of these gateways within the network bears a significant influence on network performance, techniques to "optimally" place these gateways within the network must be evolved. The study of multiple gateway placement in multi-hop mesh networks forms the next focus of this study.

This thesis ends with a discussion on further work that is necessary in this domain.

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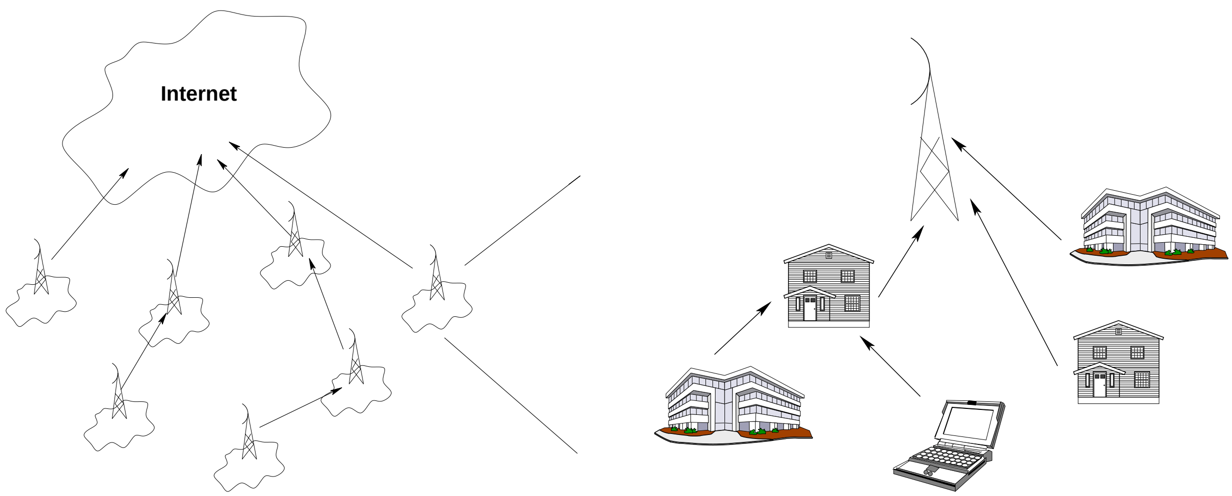
Chapter 1

Introduction

Wireless Mesh Networks (WMNs) are multi-hop wireless networks that deliver packets to the destination, by sequencing the delivery over a set of intermediate nodes in a process similar to the co-operative communication scheme used in wired Local Area Networks (LAN).

Mesh networks usually employ a two-tier communications infrastructure. The *backhaul-tier* (Figure 1.1a.) which is comprised of *gateways* is designed to handle large volumes of traffic and connect users to the internet. The *access-tier* (Figure 1.1b.) which is comprised of *nodes*, typically static wireless devices (end-users themselves) and represents user demands. Additional to serving as access-points to users, nodes also forward communication packets from other nodes to respective gateways. The number of gateways a node can transmit/forward packets to, is largely dependent on the network provider. Some WMNs accommodate nodes that forward traffic to multiple gateways while others ensure that nodes forward data-traffic to a single gateway only. In this thesis, we follow the latter approach and limit the nodes to transmit packets to a single gateway only. A gateway and its set of nodes constitute the *access tier*. Similar to the access-tier, aggregated data at the gateways may reach the internet directly with each gateway directly connected to the internet or the data could reach the internet through a set of intermediate gateways. Subsequently, the organization of gateways constitute the *backhaul tier*.

This work proposes extensions to the research project described in [10] and [9] and studies the problem of maximising the capacity in wireless multi-hop mesh networks. Specifi-



(a) Backhaul Tier

(b) Access Tier

Figure 1.1: Wireless Mesh Networks

cally, [9] proposes a method to compute the maximum throughput of an N node network with known node locations and data flows. The notion of maximum throughput in this work is the *max-min* flow rate ie., they consider maximising the minimum end-to-end flow that can be achievable in the network. The flow of traffic is invariably to and from the gateway and utilizes conflict-free link schedules for forwarding data to/from the gateway. Further, [9] also establishes the configuration of the network (in terms of link schedules, data routes, other physical parameters such as transmitter signal power and modulation-coding scheme employed by the link etc) required in order to achieve this network throughput. Nodes and gateways in this study are equipped with omni-directional antennas. Since [9] is central to this work, we start by presenting the problem formulation and some of the main results in Section 1.1. An interesting result that follows from [9] indicates that the maximum throughput of a single gateway N node mesh network is upper-bounded by $\frac{A}{N}$ (where A is the highest data-rate available in the network).

The use of omni-directional antennas in WMNs invariably leads to interference that limits the achievable throughput. In an effort to reduce the interference, the model proposed in [9] is extended to the case of smart antennas and the impact on network throughput in

WMNs is studied.

As stated earlier, the maximum throughput of single-gateway WMNs is upper-bounded to $\frac{A}{N}$ (where A is the highest data-rate of available). The maximum throughput of large single gateway WMNs hence decreases very fast as the number of nodes N increases. In order to increase the *max-min* throughput (λ) achievable for a given N-node network beyond $\frac{A}{N}$, multiple gateways within the network are necessary. However, gateway placement within the network influences the network throughput. Thus this study starts by investigating the impact of gateway placement in single-gateway WMNs on network throughput. We then study the case of networks with multiple gateways and examine two related issues: (i) gateway placement (ie., which node location must be designated as a gateway?) and (ii) node association (ie., which gateway should nodes in the network transmit/forward data to?). We examine these two problems under two network conditions modelled on (i) all access networks using a single band-width (*The Common Frequency Problem*) and (ii) each access network using a non-overlapping bandwidth (*The Multiple Frequency Problem*).

1.1 Background Work

Computing the maximum capacity of wireless networks has turned out to be an important problem for several reasons. From a technology perspective, an upper bound on the maximum throughput for a given wireless network helps us to establish benchmarks over which newer technologies and protocols can be evaluated in terms of the performance-to-cost ratio. From an engineering perspective, the limit on the maximum throughput specifies the number of gateways to be setup to serve a set of users demanding a set of services. In most networks, the cost of the gateways are critical since they primarily define overall network infrastructure costs. Careful design of a wireless network by equipping networks with an optimal number of gateways reduces infrastructure costs due to over-provisioning or reduce re-design costs due to under-provisioning of these gateways. Computing the maximum capacity of wireless networks is hence important.

As a result, several researchers have studied this problem of computing wireless capacity. The authors in [9] study the capacity of wireless networks by specifically seeking answers to two important questions: (i) What is the maximum achievable throughput for a set of nodes arbitrarily distributed in space and for a set of data flows specified as source-destination pairs? (ii) How should the network be configured in order to achieve this maximum throughput. By network configuration, they intend, the complete set of links, their physical layer parameters, the flow routes and the link activation schedules etc.

1.1.1 Problem Model

The research work in [9] starts with a set of N nodes with known positions (node positions are specified by the triplet viz., a node index $i\{i \in (1 \dots N)\}$, a $(x,\ y)$ coordinates), a single gateway and the set of data-flows (ie., only data traffic from or to the gateway). The aim is to compute the maximum network throughput available by maximising the minimum throughput achievable by any node by optimally configuring the network in terms of routing, link scheduling, physical parameters of the link (ie., transmitter power, modulation-coding scheme) etc. Since the aim is to seek "maximum" capacity results, random access wireless networks where links are activated "randomly" are not considered. Random link activations results in increased interference and collisions leading to link transmission failures. The research work hence specifies the existence of a central controller that schedules links for discrete time intervals to avoid link "conflicts".

Wireless link transmissions are not assumed to be completely error-free, instead the success of a transmission on a link is specified by the ability of the transmission to maintain the SINR above a certain threshold for the duration of the link [6]. This threshold is determined by the transmit power, modulation-coding schemes and the Bit Error Rate (BER) requirements. Hence assuming that a set of links are activated simultaneously, this model assumes that the transmissions of all these links are successful if for each of these links, the receiver receives its SINR above the threshold for the duration of the link transmission.

Since [9] also specifies the complete configuration of the network, they do not start with any specific network topology, instead they model a complete graph on the given set of wireless nodes with the vertices and edges representing the wireless nodes and links respectively. Let $\mathcal{L}$ be the set of directed links numbered $1, 2, \dots, L$ representing the set of all possible links. Let $P_l, l \in \mathcal{L}$, represent the transmitter power on link l. Since the maximum transmitter power available for each link l is limited, certain links in this complete graph are infeasible, in which case the data-rates associated with a specific radio-configuration is taken as 0. The links are assumed to be directed and each link $l \in \mathcal{L}$, is represented as (l_o, l_d), where l_o and l_d represents the originating and destination nodes respectively. Let $\mathcal{L}_i^O$ and $\mathcal{L}_i^I$ denote the set of links outgoing (and incoming) from (to) node i (respectively). As described earlier, the notion of successful link transmission is on the ability of the link to maintain a specified SINR-threshold for the duration of the link activation. Let β_l correspond to the SINR-threshold, the link l must ensure for a "success". This threshold $\beta_l, l \in \mathcal{L}$, is specified by the Bit Error Rate (BER) desired for each modulation-coding scheme on the link l. Hence for transmission on link l to be successful

$$\left\{ \gamma_l = \frac{G_{ll} P_l}{N_o + \sum_{l'} G_{l'l} P_{l'}} \right\} \geq \beta_l \tag{1.1}$$

γ_l corresponds to the SINR computed on link l. G_{ll} denotes the gain from the transmitter to the receiver of link l, $G_{l'l}$ denotes the gain from the transmitter of l' to the receiver of l, and N_0 denotes the noise power in the operating frequency band. The gains $G_{\{..\}}$ are assumed to be known and fixed. Details on modeling interference using BER or SINR, are explained in [11]. In this research work, the channel gain G_{ll} are modelled as isotropic path loss, where the channel gains between two points x and y is specified by the relation

$$G_{xy} = \left(\frac{|x - y|}{d_o} \right)^{-\eta} \tag{1.2}$$

where η is the path loss exponent, usually between 2 and 4; and d_o represents the far-field cross-over distance.

Since this model incorporates multiple modulation-coding schemes, let z_l represent the modulation-coding scheme available on link l and $\mathcal{Z}$ represent the set of available modulation-coding schemes. The modulation-coding scheme available for each link l is abstracted into data-rate c_l, where depending on the modulation-coding schemes on the link l, a specific value is associated for the data-rate c_l. Hence, depending on the set of modulation-coding scheme available at each node, multiple links (each link associated with a specific modulation-coding scheme) are possible between a transmitter-receiver node pair (or pairs of vertices in the complete graph).

The success of link transmission is dependent on the ability of the link l to maintain its SINR above a threshold β_l (refer Equation (1.1)). This indicates that multiple links can be simultaneously activated provided that each link l maintains the threshold β_l for the duration of the activation. Hence let $\mathcal{I}$ denote this set of independent sets of links, which characterizes the simultaneous operation of the sets of links based on the interference caused by the links to one another. Hence denoting the subset of links by an L-dimensional vector x, where $x_l = 1$ implies the link $l \in x$ and $x_l = 0$ implies $l \notin x$, the set of independent sets $\mathcal{I}$ is given by:

$$\mathcal{I} = \left\{ x : \frac{G_{ll}P_l}{N_0 + \sum_{l',l\neq l'} G_{l'l}P_{l'}x_{l'}} > \beta_l x_l, \forall l \in \mathcal{L} \right\} \tag{1.3}$$

Let $\mathcal{I}_l$ represent the set of independent sets, a link l belongs to. Let $\alpha = \{\alpha_k, k \in \mathcal{I} | \sum_{k\in\mathcal{I},\alpha_k\geq 0} \alpha_k = 1$ represent the link activation schedule, k is any generic independent set and α_k represents the fraction of time, the independent set k is active. A flow is specified by a source-destination pair and the set of flows is denoted by $\mathcal{F}$. Flows in the set $\mathcal{F}$ are numbered $1, 2, \ldots, M$. For each flow $f, \{f \in \mathcal{F}\}$, let f_s and f_d denote the source node and the destination node respectively. Let x_l^f denote the amount of flow f on link l and λ_f, the throughput on flow f.

With the network model and the notion of "independent sets of links" now defined, the solution to this problem of maximising the capacity lies in selecting appropriate independent sets of links such that the data transferred from each node on these links are maximised. Hence the problem of capacity and optimal configuration can then be modeled as the following optimization problem:

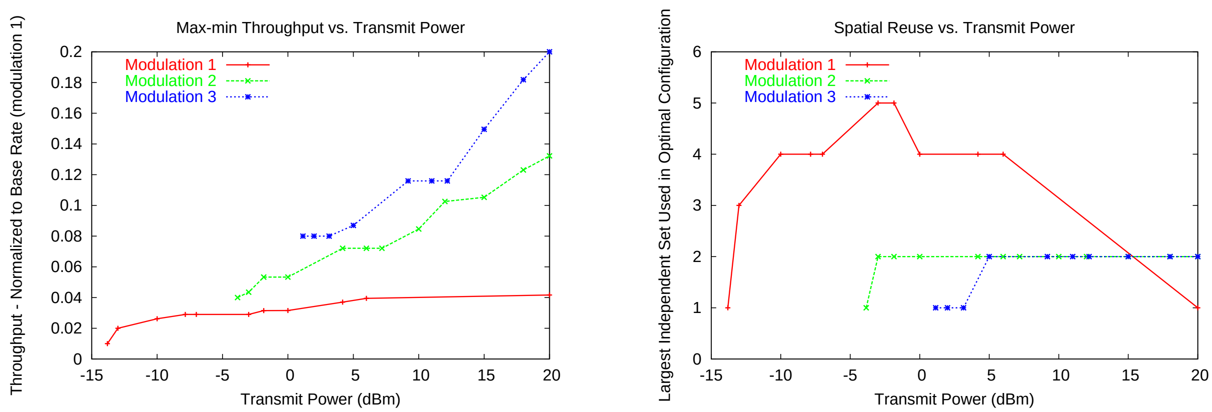
$$\begin{aligned} &\max\ \lambda && (1.4)\\ &\textstyle\sum_{l\in\mathcal{L}_i^o} x_l^f - \sum_{l\in\mathcal{L}_i^I} x_l^f = \begin{cases} 0 & i \notin \{f_s, f_d\} \\ \lambda_f & i = f_s \\ -\lambda_f & i = f_d \end{cases} \\ &\qquad\qquad i = 1, \ldots, N, f = 1, \ldots, M \\ &\textstyle\sum_{f\in\mathcal{F}} x_l^f \leq c_l \sum_{k\in I_l} \alpha_k \quad l = 1, \ldots, L \\ &\textstyle\sum_{k\in\mathcal{I}} \alpha_k = 1 \\ &0 \leq \lambda \leq \lambda_f \qquad f = 1, \ldots, M \end{aligned}$$

From Equation (1.4), the objective is clearly to maximise the throughput λ (the throughput λ in the objective function is the throughput associated with each flow that needs to be maximised. The optimization model described in Equation (1.4) uses the *max-min* throughput to accomplish this.) under the following constraints. The first specifies the flow conservation ie., unless a node i sources or sinks data-flow, the total amount of flow handled by this node is zero. The next specifies the capacity conservation constraint ie., a link l can handle only so much of the total flow as the data-rate c_l corresponding to a specific modulation-coding scheme and the discrete time interval for which the link l is active over all the flows. The next constraint specifies that the sum of activation of all the "independent sets" $I_k, k \in I$ must equal 1.

1.1.2 Results

Several interesting results follow from this research work. A few of them are briefly mentioned in this section. The optimization framework indicated in the previous section can be translated into a computational tool for accurately computing the maximum throughput capacity and the required configuration necessary to achieve it for any N-node network. Figure 1.2a., indicates one such result for the case of a 5×5 grid with a single-gateway placed in node-position 1. All three modulation schemes illustrated in Figure 1.2a., are defined for a BER requirement of 10^{-6}. Subsequently for *Modulation 1*, this BER requirement corresponds to an SINR threshold (β_l) of 10 dB and is associated with a data-rate (c_l) of 1. The maximum throughput (normalized) achievable for the 24-node network is 0.0416 or 1/24. Similarly the BER requirement of 10^{-6} for *Modulation 2* and *Modulation 3* corresponds to the SINR-threshold (β_l) of 100 dB and 1000 dB respectively. Subsequently data-rates (c_l) of 4 and 8 are associated with *Modulation 2* and *3* respectively. Hence the maximum throughput (normalized) achievable increases to 0.167 and 0.333 corresponding to $4 \times \frac{1}{24}$ and $8 \times \frac{1}{24}$ respectively. Note that the maximum achievable throughput increase associated with *Modulations 2* and *3* over *Modulation 1* incurs greater transmitter power requirements. Clearly, the maximum upper-bound is limited to $\frac{A}{N}$ (where A is the maximum data-rate available in the N node network).

From the throughput curves in Figure 1.2a., it is also evident that while the maximum throughput of a N-node network is upper-bounded to $\frac{A}{N}$ (where A is the highest data-rate available in the network), the throughput at lower powers is considerably reduced. Two factors influence this reduced throughput: (i) transmit signal power used does not create



(a) Throughput Plot (b) Spatial Reuse Plot

Figure 1.2: a. Variation of λ^* with transmit power (in dBm) b. Variation of Spatial-Reuse with transmit power (in dBm)

longer links, hence throughput is considerably reduced since data needs to be relayed on intermediate nodes. (ii) the use of low transmit power makes links more vulnerable to interference and hence spatial re-use significantly decreases in lower powers resulting in reduced throughput.

Finally, spatial reuse plots corresponding to *Modulations 1, 2* and *3* have been plotted as a function of transmit power P in Figure 1.2b. For very low powers in the case of *Modulation 1*, spatial reuse is just 1, resulting in only singletons (independent sets of size 1) being scheduled. The susceptibility of links to interference at extremely low powers contributes to this behaviour. As power is increased, the spatial re-use improves, since increased transmitter power not only enables strengthening of links (due to higher SINR), but independent sets that were infeasible at lower powers now become feasible due to increased transmitter power. At high transmitter power corresponding to links that span the complete network, spatial reuse again decreases to 1, since all nodes are able to communicate with the gateway directly and the presence of single-radio on the gateway ensures that only one node can communicate with the gateway at any given instant.

Chapter 2

Network Performance: The Impact of Directional Antennas

Improving the capacity of wireless networks by employing smart and innovative schemes has been an important topic of study for several researchers worldwide. As a consequence of the research work in [9], we now know that the maximum throughput of a single gateway, scheduled WMN is upper-bounded by $\frac{A}{N}$, (A is the highest operating data-rate of any link) where N is the number of nodes in the network (not including the gateway). For instance, for a WMN of 36 nodes and 1 gateway, with an operating data-rate of 100 Mbps (expected in IEEE 802.16), the maximum achievable flow throughput is upper-bounded by 100/36 Mbps or 2.8 Mbps.

An important factor that usually affects wireless networks and limits their performance is interference, especially due to the omni-directional nature of transmissions. As seen in [9], the upper bound on throughput is achieved for very high values of transmit power and for low to moderate powers, the achievable throughput turns out to be considerably lower. In general, the use of omni-directional antennas results in poor range for a given transmit power, thereby leading to longer paths, and higher relaying load on the links close to the gateway. Further, the distribution of energy in directions other than the required direction creates interference that limits the number of links that can be active simultaneously. An efficient and robust method to improve network throughput at a given power is by using directional antennas. By focussing the energy within a given envelope, directional antennas increase transmission range, reduce interference and consequently allow for better throughput.

Conventional directional antenna technology has several drawbacks. Some of them are: (i) *Prohibitively high steering time*: Broadband networks infrastructure must support high throughput data links and high speed switching interface between nodes. Directional antennas with their superior link quality are capable of maintaining high capacity links but the network throughput is bottlenecked by the delay involved in mechanically steering and accurately positioning these antennas between appropriate nodes. (ii) *Power consumption*: The use of mechanically steerable antenna consumes large amounts of power to make it practical to be deployed in community networks where the emphasis is on the use of low power hardware. The possibility that some of these nodes employ battery based power sources makes it infeasible to use mechanically steerable antennas. As expected these limitations have forced researchers to define and build new antenna technologies that deliver on the performance of directional antenna while overcoming much of their drawbacks. In recent years, *Smart Antenna* technology has made great strides in delivering this promise.

Several technologies contend as *smart* antennas by incorporating some *intelligence* in their working principle. *Intelligence* in most antenna technologies invariably involves multiple antenna elements. Depending on how the antenna elements function with respect to other co-existing antenna elements, *smart antenna* can be classified as either *Phased Array antenna system* or *Switched Beam antenna systems*.

In *Phased array* technology, beam steering is achieved by constantly changing the excitation phase feeding the antenna elements. Since the orientation of the main-lobe is a function of the phase fed to the antenna elements, a phase change results in a beam steer. In *Switched Beam* antenna technology, steering is achieved by selectively switching specific antenna elements pre-oriented to specific directions. Other *smart* antenna technology use a combination of either of these two technologies along with sophisticated signal processing to isolate or null noise, improve SNR (Signal-to-Noise Ratio) of the intended signal etc. In this thesis however, the term *smart* is used for antenna systems which (i) radiate power not in all directions, but confined within a certain angle of a particular direction, and which (ii) have the ability to orient their beams electronically and quickly, in any particular direction. The use of such antennas result in the following gains:

1. For the same power, smart antennas can provide higher range, and therefore shorter paths, lowering the relaying burden on the links close to the gateway.

2. For the same range, smart antennas can operate at lower powers, and reduce the interference, thereby improving the spatial reuse.

3. In a scheduled WMN, the ability to steer antenna beams helps ensure the alignment of transmitter and receiver beams, thus maximizing the gains from directionality. Unlike omni-directional antennas, resolving directions to steer and align smart antennas is fairly difficult owing to the problem of "deafness" in smart antennas. However the use of scheduled networks where antenna directions are pre-computed and executed in a time-scheduled basis makes scheduled networks particularly suited for smart antennas.

This chapter is organized as follows. I begin by introducing related work in this area and go on to describe the problem completely by explaining the antenna model and the problem formulation. The results are described next, substantiated by relevant data. I briefly describe existing antenna technologies and evaluate these technologies in a WMN setting before concluding by summarizing the results.

2.1 Related Work

Significant research has been conducted on the capacity of mesh networks employing directional/smart antennas both in terms of the asymptotic capacity scaling [13, 14, 15] and by proposing different protocols to increase the network capacity [17, 18, 19, 20]. In [15], the asymptotic capacity bounds for ad-hoc networks derived by Gupta and Kumar [16] for omni directional antennas have been extended to the smart antennas modelled using a simple flat-toped antenna model, a phased array model and an adaptive array antenna model. Although the capacity scaling is shown to essentially remain the same, the authors note that by scaling the antenna parameters such as the number of antenna elements, the capacity could be improved, but not in all cases. In [14], the authors have specified that the capacity scales by a factor of $\sqrt{\frac{2\pi}{\alpha\beta}}$, in wireless ad-hoc networks; where α and β are the beam-widths of the transmitting and receiving antennas. In [13], the asymptotic capacity of a random network under an ideally sectorized directional antenna model, is shown to scale as $\Theta(\sqrt{n \log^3 n})$, assuming the beam-width can be made arbitrarily small, and that receivers can decode multiple non-overlapping beams simultaneously. Interestingly, despite having such sophisticated directional antennas at one's disposal, the capacity improvements are only of the order $\Theta(\log^2 n)$ over the Gupta-Kumar bound [16].

In [20], the authors have proposed a Directional Busy Signal Multiple Access (DB-SMA) MAC protocol as a means to achieve significant improvement in the throughput of the ad-hoc networks. Their protocol also uses a more general directional antenna model than the ideally sectorized antenna model used in [18]. In [18], the authors have proposed an adaptive MAC protocol where each node maintains the dynamically changing neighbourhood information in order to decide on the direction, nodes employing directional antennas can communicate. Some MAC protocols proposed for smart antennas include [18] for ideally sectorized antennas, [17] for switched-beam antennas, and [19] for phased array antennas. [18] proposes a multi-hop RTS MAC protocol (MMAC) for directional antennas. Through simulations on a 5×5 grid and a random network for different instances of routes, the authors show a throughput increase of up-to 400% over IEEE 802.11. In comparison to these works, our analysis computes exactly the maximum throughput achievable by the network employing directional antennas for specific topologies under scheduled network operation. We do not seek results in the asymptotic scaling sense or by proposing random access protocols. We base our results using available physical layer technologies and model the interference on the notion of conflict-graphs by specifying sets of mutually interfering links that cannot be used simultaneously.

2.2 Antenna Model

Our main focus in this chapter is to understand the impact of directional antennas in wireless networks. Hence its important that the results and insights we develop during this exercise can be applicable to existing directional antenna technologies. We do not intend to realistically model directional antennas (although such a model is quite necessary) for several reasons. (i) Our focus of work is to study the impact of directional antennas on WMN and to establish an upper bound on the network throughput. We are not interested in evaluating different directional antennas and their behaviour in WMN and any such attempt to use *specific* directional antenna model will deviate from our main goal. (ii) Several directional antenna technologies exist and most, if not all of these, can be appropriately used in WMN. The selection of the *right* directional antenna is also influenced by other parameters like equipment costs, operating complexity, frequency of operation etc.; none of which form our study goals. It is hence important that we use a very generic directional antenna model, at the same time ensuring that our model is in-line with our definition of *smart* antenna.

Also, in the network setup, we envision that each node is mounted with such a *smart* antenna system. In characterising our antenna, we assume that our antenna has some intelligence to correctly switch its radiation beam towards an incoming signal, although we make no assumptions on the type of algorithm or the method, the antenna system employs to determine the direction. We also make no assumption on the antenna capable of incorporating a null for Signal Not Of Interest (SNOI). We assume direct line-of-sight communication and intend that the antenna can distinguish between direct rays and ground-reflected rays appropriately. The term *smart* and *directional* have been used inter-changingly in this chapter.

In our model, we consider Smart antennas as directional antennas whose beams can be steered to any pre-computed direction to facilitate perfect antenna alignment between the transmitter and receiver nodes of each link in the given independent set. Each of the smart antenna equipped nodes can accomplish such steering independently of the rest. Further, we also assume that antenna steering and alignment is very fast and delays associated with antenna steering are negligibly small. Our antenna model is characterized by two important parameters: *gain* (Γ) and *beam-width* (θ) which can be computed from the aperture a and the operating wavelength ζ as [22]:

$$\Gamma = \epsilon(\frac{\pi a}{\zeta})^2 \tag{2.1}$$

$$\theta = \frac{70\zeta}{a}$$

where ϵ is the antenna-efficiency, usually assumed equal to 55%. Clearly, an antenna with a gain (Γ), at a given transmitter power (P) can reach multiple nodes in the network.

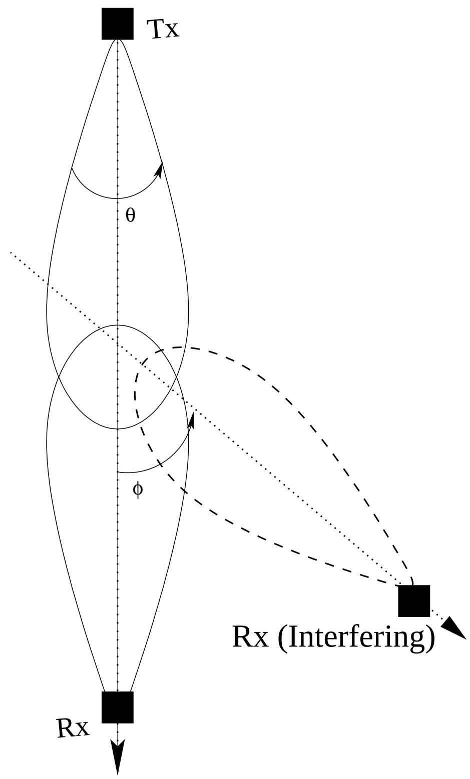


Figure 2.1: For perfectly aligned smart-antennas, the total gain is Γ^2, For the case of antennas with an angle ϕ between their alignments, the total gain perceived by the receiver is indicated in Equation (2.3). Note: The arrows indicate the direction of transmission.

Some of these nodes however will never be part of the "optimal" routes as determined by the "optimal configuration" of the network and hence some of these nodes will never be used for relaying data-traffic from a node i. However, for all nodes that are part of the "optimal routing" or constitute the next hop node (as determined by the optimal-routing policy), information on orienting smart antennas to favour precise alignment between transmitting and receiving nodes are pre-computed. The central scheduler uses this information at pre-determined times to instruct corresponding nodes to orient smart antennas in precise and specific directions.

2.2.1 Gain

In our smart antenna model, we neglect side-lobes and back-lobes and assume that energy is concentrated within the main-lobe. Consequently, the gain is zero outside the beam-width. In our network model since all antennas have uniform beam-width, the gain of the transmitting antenna (Γ_t) is identical to the gain of the receiving antenna (Γ_r). Hence let Γ be representative of the antenna gains. Moreover, depending on the orientation of the transmitting and receiving antennas, the gain Γ within the beam-width is a variable parameter. Along the axis of the beam (the transmitting and receiving antenna are aligned accurately), the gain of the directional antenna is Γ, while at an angle of ϕ with respect to the axis of the beam, the gain is lower by a factor of $16^{\frac{\phi}{\theta}^2}$. At the receiver, the power is computed

$$P_r(d) = \frac{P_t \cdot \lambda^2 \cdot \Gamma_t \cdot \Gamma_r}{4\pi^2} \cdot \left(\frac{d}{d_o}\right)^{-\eta} \tag{2.2}$$

where $P_t, P_r, (\Gamma_t, \Gamma_r)$ represents the transmitter and receiver power (gain) respectively; d_o is the far-field cross over distance and η is the path loss exponent and d represents the distance of the receiver-transmitter separation. Hence for perfectly aligned antennas, assuming that all nodes in the network are the same, the total gain is $\Gamma_t \times \Gamma_r = \Gamma^2$ while total gain for transmitting-receiving antennas aligned with an angle ϕ is

$$\Gamma_t \cdot \Gamma_r = \frac{\Gamma^2}{16^{(\phi^{tx}_{l'l}/\theta)^2} 16^{(\phi^{rx}_{ll'}/\theta)^2}} \tag{2.3}$$

2.2.2 Beam-width

As explained earlier, we do not consider side-lobes and/or back-lobes in our antenna model. Our antenna model incorporates a beam steering although the beam-width remains constant as the antenna is steered. The constant beam-width implies a constant gain Γ as the antenna is steered.

Note:
Several other antenna models can be found in the literature. Some of these are:

1. Idealized Antenna Model
   This antenna model is characterized by a constant gain C within the beam-width, and zero gain outside the beam-width. Typically, if Γ represents the antenna gain, θ represents the antenna beam-width and ϕ represents an arbitrary value, then the gain Γ is given by
   $$\Gamma = \begin{cases} C, & \phi \leq \theta \\ 0, & elsewhere \end{cases}$$

2. Flat-topped Antenna Model
   This antenna model is characterized by a constant gain within the beam-width and a smaller gain outside the beam-width. Hence, the gain Γ is given by
   $$\Gamma = \begin{cases} C, & \phi \leq \theta \\ \beta C, \ elsewhere & (\beta << 1) \end{cases}$$

2.3 Network Model

2.3.1 Scheduled Wireless Mesh Networks

In this chapter, we consider the case of centrally scheduled mesh networks as in [9]. This assumption works well in this context since we are seeking "maximum" capacity results. The use of scheduling to co-ordinate link transmissions ensures no packets are lost due to collisions and hence the throughput obtained represents the maximum throughput or the *upper-bound*. The use of scheduled networks in directional antennas alleviates in principle, a major drawback associated with directional antennas i.e., *deafness*. A problem associated with directional antennas is the inability of the source (transmitting) node to resolve a free destination (receiving) node from a busy destination node. This problem is called *deafness* since the directional antenna employed by the nodes is deaf to all directions except the direction in which it is transmitting data. The use of scheduled network with pre-determined link activation schedules enables smart antenna equipped WMNs to precisely align receiver and transmitter antennas thus maximising the gains from directionality and reducing interference. Further the nature of the traffic can be either uni-directional (nodes are uploading traffic to gateways or gateways are downloading traffic to nodes) or bi-directional [12].

2.3.2 Optimization Model and the Computational Framework

We extend the computational tool based on the optimization framework proposed in [9] to incorporate directional antennas. From the optimization model indicated in Section 1.1, it is clear that the existing model serves well in the case of directional antennas as well.

Although the optimization model remains identical to the model proposed in [9], the computational tool based on this framework requires substantial changes to incorporate directional antennas in all the nodes and gateways. Modelling directional antennas has already been explained in Section 2.2. It is well known that the use of directional antenna increases spatial reuse in the network since interference is reduced. Such an advantage; in our study translates in increasing the bound of the size of the maximum independent set in the network.

In [9], it has been shown that in general, computing the maximum throughput of an arbitrary network is an NP-hard problem [12]. However [9] also indicates that it is possible to solve the problem exactly, under certain assumptions. Under these assumptions, it is possible to establish a bound on the size of the maximum independent set in the network. Then, the numerical technique used in [9] for the case of omni-directional antennas, is that of enumerating the set of independent sets, by using this bound. This is accomplished by only checking the "independence" of all subsets of $\mathcal{L}$, of a size smaller than the bound.

For this approach to work in the case of smart antennas, we need to derive a bound on the size of the maximum independent set in the network when smart antennas are used. We are however, unable to find a bound tight enough to be used. Instead, we take the following approach. Rather than attempting to solve the problem exactly, we solve it approximately, by enumerating all independent sets of a size smaller than a complexity parameter we term `MAXISET`. By increasing the value of `MAXISET`, the accuracy of our results can be improved. There are two advantages to using this approach: (i) the throughput we obtain through this approach is clearly always a lower bound on the actual achievable throughput; and (ii) the parameter `MAXISET` introduces a trade-off between complexity and performance. The higher the value of `MAXISET` the more accurate the results, at the

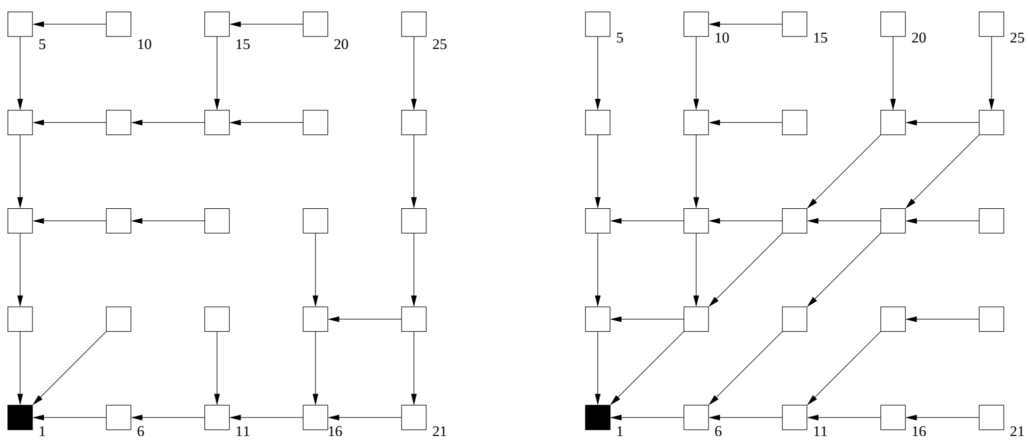


Figure 2.2: Optimal Routing for a 5×5 grid employing: (i) omni-directional antenna with transmit power -7.75 dBm (left); (ii) smart antennas with beam-width 52^o and transmit power -22.48 dBm (right).

cost of increased computational complexity of enumerating larger sized subsets. We do not claim optimality of the numerical results we present, for smart antennas, but we feel this is a reasonable approach because even with modest values of `MAXISET`, we are able to demonstrate considerable gains in using smart antennas. In this study, we use a MAXISET value of 8 indicating that up-to 8 links can be scheduled simultaneously.

2.4 The Impact of Directional Antennas: Results

In order to evaluate the performance of directional antennas in WMNs, we choose the following computation environment. We consider a 5×5 grid topology with 24 nodes and 1 gateway as indicated in Figure 2.2. The gateway is placed at the bottom left corner. This regular grid topology features an inter-node separation of $8m$ along the rows and columns of the grid. For this scenario, all nodes use the same power and the same modulation scheme. The modulation scheme requires a SINR threshold of 10 dB to guarantee a BER of 10^{-6}. For the sake of simplicity, we consider uni-directional traffic, where we associate each node with a flow that originates with the node and terminates at the gateway. The computational tool however is quite capable of handling bi-directional traffic as well. The

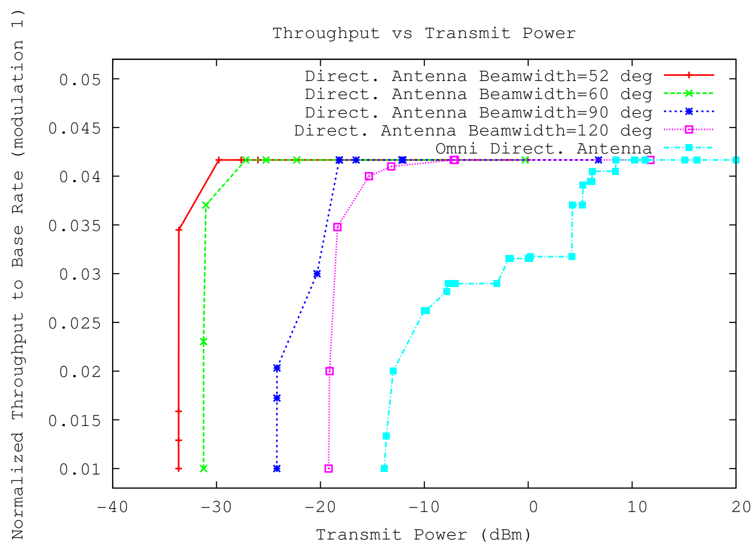


Figure 2.3: Variation of λ vs Transmit Power (dBm)

variation of the network capacity as a function of transmit power is illustrated in Figure 2.3 by using the computational and modelling techniques described in Sections 1.1 and 2.2.

2.4.1 Omni-directional antenna

For the case of single-gateway WMN employing omni-directional antennas, [9] establishes the upper bound on the maximum throughput to $\frac{A}{N}$. This throughput however, is achieved at higher power. For low to moderate powers, the maximum throughput actually fares much worser. From Figure 2.3, it is clear that the throughput achieved at lower powers, especially at powers when the network *just gets connected* is less than one-fourth of the maximum achievable throughput. Increasing the transmitter power marginally leads to dramatic throughput improvements to about 60% of the maximum at -8 dBm. Increasing the transmitter power further leads to a slow but steady rise, with the maximum throughput ($\frac{A}{N}$) achieved at 8.46 dBm, a full 22.32 dBm after the network becomes first connected. Clearly this high throughput is achieved with high power expenditure.

Figure 2.2a., illustrates the optimal routing used by the network at a transmit power of -7.75 dBm. At this transmit power, the range of the nodes is sufficient to reach the diagonal node and yet, the optimal routing depicts some interesting facts. Far from using

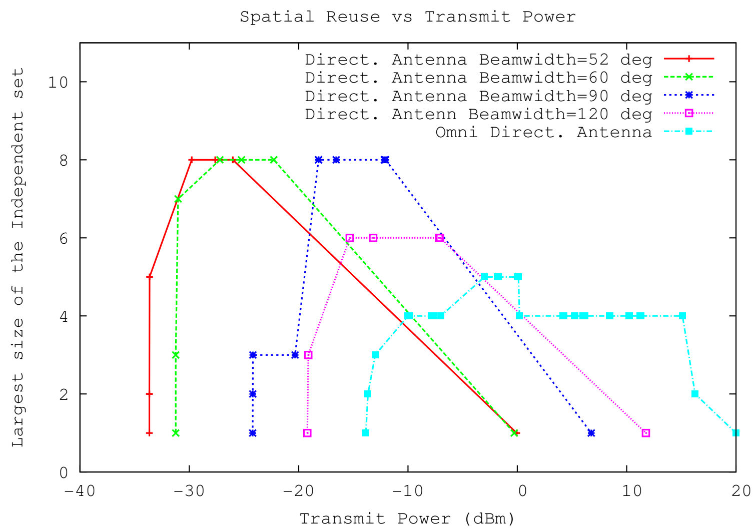


Figure 2.4: Variation of Spatial Reuse with Transmit Power (dBm)

the shortest path by employing diagonal links, the nodes on the periphery of the grid route the data along the periphery using more hops in the process to reach the gateway and at the same time avoiding internal nodes to forward data traffic. Such a routing scheme has been called in [9], "interference-avoiding" and can be attributed to the high-interference caused by use of omni-directional antennas. Such a routing scheme increases the relaying load on the links to the gateway and has a detrimental effect on the throughput. This also perhaps explains the slow increase in the throughput plot of the omni-directional antenna from moderate to high powers.

2.4.2 Directional Antenna

One of the key reasons of employing directional antennas in WMNs is to improve network performance by harnessing the advantages associated with reduced interference. As expected, directional antennas in our study contribute to increase network throughput. Network throughput as a function of transmit power is plotted for various antenna beamwidths in Figure 2.3. It is evident that the maximum network throughput for a WMN with N nodes is still upper-bounded by $\frac{A}{N}$ (where A is the maximum data-rate available) with smart antennas irrespective of the antenna beam-width considered. This result specifically, is due to the fact that we are considering single-gateway WMNs, where gateways and nodes are equipped with single-radio interfaces capable of communicating with one link (or a node) at any given time. The network throughput is maximised when all nodes are able to communicate with the gateway within one hop (thereby removing the need to relay load to intermediate nodes). Ensuring that all nodes get to communicate with the gateway implies that in 1 unit time interval, the gateway must ensure that the n nodes are each allocated $\frac{1}{n}$ discrete time unit.

Hence directional antenna do not contribute to improving the throughput bound of omni-directional antenna. However, the greatest advantage of using smart antennas is in low powers, where marginal increases in transmit power results in substantial gains in network throughput. For example, consider the plot of directional antenna with antenna beam-width of 52^o. Network connectivity is achieved at -33.65 dBm. A slight increase in transmitter power to -33.63 dBm improves the network throughput by 70.9%. An increase made possible for a 0.02 increase in transmit power. Thus for power critical WMNs, directional antennas provide clear cut advantages both in terms of power-savings (the network connectivity using directional antennas is achieved at -33.65 dBm compared to -13.85 dBm for the case of omni-directional antennas; a full 20 dBm savings in power) and the throughput that can be extracted for marginal increases in power. Further, as the antenna beam-width is increased, the upper-bound of $\frac{1}{n}$ still persists but two points are worth mentioning. (i) Reduced savings in power, evident from the fact that the plots are moving closer to the omni-directional antenna as the beam width is increased. (ii) The throughput gains for marginal increases in transmit power is no longer substantial as evident by comparing plots of smart antennas with beam width 52^o and 90^o. As referenced earlier, a 0.02 dBm increase in the transmit power achieves a 70.9% improvement in throughput for smart antennas with 52^o beam-width, while to achieve the same throughput improvement for smart antennas with 90^o beam-width, the transmit power needs to be increased by 5.2 dBm.

In our simulation environment, we have fixed the bound on the size of the maximum independent set i.e., MAXISET to 8. In-spite of possibly choosing a suboptimal value for MAXISET, the gains of using smart antenna are apparent from Figures 2.3 and 2.4. In Figure 2.4, it is quite clear that the use of directional antenna significantly improves spatial reuse, although at very high powers, spatial reuse reduces to 1, since at these powers, all nodes are able to communicate with the gateway directly

Figure 2.2b, illustrates the optimal routing plot for a smart antenna with an antenna beam-width of 52^o corresponding to a transmit power of -22.63 dBm. This specific transmit power corresponds to a transmission range of 11.41m, similar to the case of an omni-directional antenna with transmit power of -7.75 dBm illustrated in Figure 2.2a. In contrast to Figure 2.2a, the smart antenna routing plot indicates the *frequent* use of diagonal links thus enabling most nodes in the network to choose a direct path to the destination (gateway). The directed beam of the smart antenna results in less interference and hence nodes, on the periphery of the grid network no longer choose an "interference avoiding" path, but instead route their data traffic through the grid itself.

As we saw earlier, owing to their directionality, smart antennas provide a gain of Γ with respect to omni-directional antennas. Hence, a smart antenna can achieve the same transmission range for significantly lower powers ($P \rightarrow \frac{P}{\Gamma^2}$). Also for the same power, smart antennas can provide connectivity at increased inter-node separation ($D \rightarrow \Gamma^{2/\eta} D$).

2.5 A Note on Smart Antennas

Antenna arrays are often used to direct radiated power towards a desired angular sector. As explained earlier, antenna arrays can be used either to steer a directed beam to a particular position or can be used to switch a beam to a desired direction. We consider two interesting smart antenna technologies depending on how beam steering is achieved.

2.5.1 Phased Array Antennas

Phased array antennas exploit the relative displacements of the antenna array elements to introduce phase shifts in the radiation vector and to radiate power in a given direction [21]. By constantly changing the excitation phase of the array elements, beam-steering can be successfully achieved. The ability of phased array antennas to control beam steering to any required direction achievable at high speeds makes these antennas an invaluable addition in WMNs since: (i) networks capable of high throughput can be designed using these

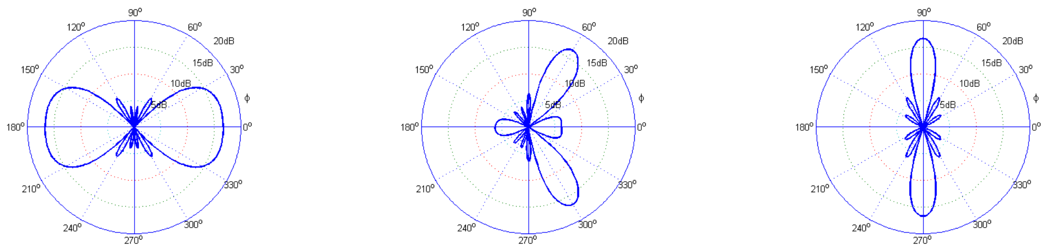


Figure 2.5: Phased Array Antenna: a. Azimuthal gain patterns of a 6-element uniform array with the main-lobe at a. 0^o b. 60^o c. 90^o Clearly, the beam steer has no effect on the main-lobe but side-lobes and back-lobes antenna patterns and their number have changed.

antennas, (ii) network design can also be simplified, since a single phased-array antenna type can equip all the constituent nodes and gateways in WMNs.

However, the use of phased array antenna in WMN raises important design concerns. Incorporating phased arrays in WMNs also needs to factor in the effects of side-lobes and back-lobes. The side-lobe and/or back-lobe can have a non-negligible effect on network performance since they add on to network interference. In the case of phased array antennas, the number of elements constituting the antenna array, their arrangement and relative displacements along with the phase determine the overall radiation pattern of the antenna and in several cases introduce, remove or modify side-lobes and/or back-lobes in the radiation pattern [23]. Modelling behaviour is particularly hard since the resulting model needs to accurately determine the complete and changing radiation pattern for every beam steering. In Figure 2.5, the azimuthal gain pattern of three different phased array antenna are plotted. As can be noticed, as the beam is steered from end-fire ($\phi = 0^o$) to broadside ($\phi = 90^o$), the side-lobes and the back-lobes in the antenna radiation pattern changes. The variation of the side-lobe gain for a 6 element antenna array with each element separated by a 0.5 wavelength of its channel frequency is plotted in Figure 2.6 as the antenna array is steered from 0^o to 60^o in 10 steps. Although the main-lobe gain remains a constant, this figure clearly indicates the variation in the side-lobe gain and the difficulty associated with incorporating this model in WMN design.

2.5.2 Switched Array Antenna Systems

Switched arrays [24] operate by providing overlapping beams that cover a required angular sector. Depending on the direction of the incoming signal, a control unit determines the best beam that is aligned to the incoming signal and switches on the beam to start communication. Such an antenna system has considerable difficulties in offering the full gain for incoming signals that are in a direction between two overlapping beams and represents a severe limitation on the use of these antennas. Compared to phased array systems, these antennas are cost effective [25] and offer fixed radiation patterns in *all* directions. The rigid switching structure of the switch array system where incoming signals unaligned with pre-determined beams result in reduced gain often bottleneck their performance in WMNs. This might also require configuring the constituent beams on the nodes, on a per-node basis, depending on the topology.

In Section 2.2, we have described our antenna model. Our smart antenna model supports extremely fast steering and alignment in switching between different pre-computed paths. Further, we also indicate that this model enables only the main-lobe and discard modelling the side-lobe and/or back-lobes. Clearly an antenna with such high capabilities is unrealistic. However, not withstanding these technicalities, our goal throughout this study has clearly been to establish upper bound in network throughput and get valuable insights on the behaviour of spatial reuse and routing in WMNs employing smart antennas. Incorporating realistic smart antenna models is clearly a requirement if practical WMNs using smart antennas are to be designed.

2.6 Conclusion

Our efforts to quantify throughput of WMNs employing directional antennas has given us interesting results. By extending the computational tool based on the optimization framework proposed in [9] to incorporate directional antennas, we have shown that the maximum throughput is upper bounded by $\frac{A}{N}$ (normalised with respect to the highest operating data-rate A), where n is the number of nodes in the network (not including the gateway). This result is identical to the result obtained in [9] using omni-directional antenna. Although significant power savings accompany directional antennas as seen in the

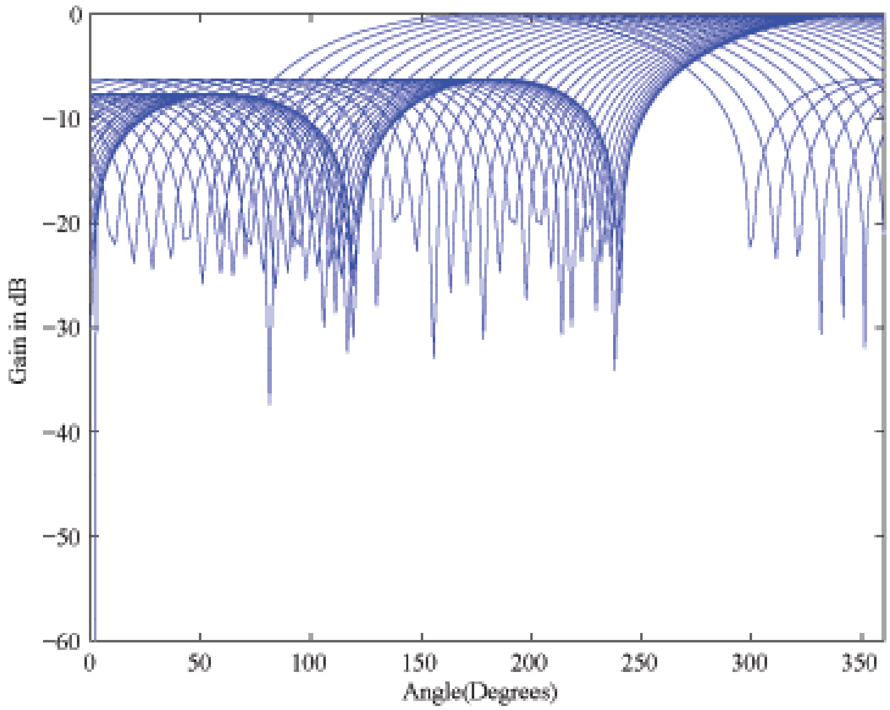


Figure 2.6: Side-lobe antenna patterns as the phased array antenna is steered from 0^o to 60^o. Note the variation in the side-lobe gain which makes it difficult to design smart-antenna equipped WMNs.

earlier throughput plots, it is particularly significant that the upper bound in itself remains unchanged. Hence if power is not a design concern, then substantiating WMN migration from omni-directional to directional antennas is difficult; especially with the increased difficulty in deploying smart-antenna equipped WMN However, the greatest advantage of using directional antenna is in the low to moderate power range, where significant improvement in throughput can be achieved for marginal increase in the transmit power.

The upper bound of $\frac{A}{N}$ for N-node single-gateway WMNs employing directional antenna also motivates us to come up with alternate schemes to improve network throughput, especially if the services demanded require throughput capabilities greater than $\frac{A}{N}$. The study of these schemes forms our next chapter.

Chapter 3

Gateway Selection Algorithms

Internet Service Providers or ISPs have long struggled to balance deployment costs with the unprecedented demand for broadband access from both commercial and residential users. Consequently, several researchers have explored varied paths in improving the performance of mesh networks. Broadly, their approach can be classified into 3 main categories: (i) Improving the throughput of existing deployed networks by equipping networks with smart antennas etc., (ii) migrating to other or newer standards/technology that promise higher throughput and (iii) adding more gateways points and using existing technology to improve network throughput. From our study on smart antennas and their influence on network performance, primarily throughput, it is evident that smart antennas improve throughput for a certain power, but certainly, do not change the upper bound on the maximum achievable throughput (λ). Hence smart antennas equipped WMNs may not be the right approach for improving network throughput beyond $\frac{A}{N}$ (A is the highest data-rate available in the N node mesh network). The emergence of new standards is usually associated with new technologies. Incorporating new technologies and replacing existing ones is a very complex and drawn out affair demanding efficient management of available resources (primarily costs and manpower) with the difficulties associated in planning and logistics, costs of re-training, choice and familiarity to new hardware etc. Clearly, migrating to new technologies is not a very easy decision. Compared to these, a robust strategy to improve network throughput simply involves the addition of more gateways. Mesh networks, in particular, are well poised for this approach since (i) in most cases, data aggregation points

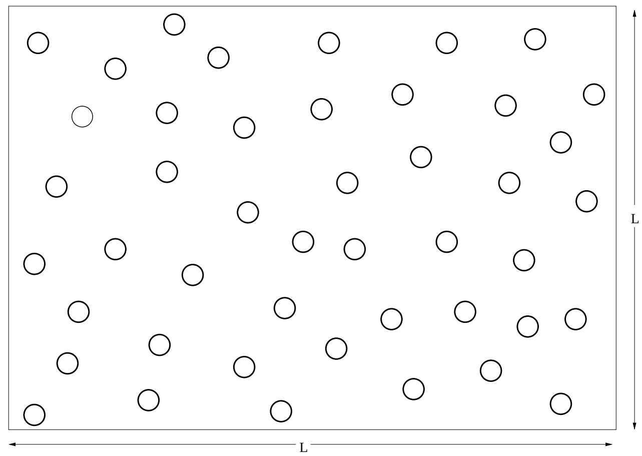


Figure 3.1: N nodes arbitrarily distributed within an $L \times L$ area.

or gateways in mesh networks are nodes themselves with small changes to the hardware that enables them to connect to the back-haul tier. (ii) The tiered organization of mesh networks simplifies enabling nodes as gateways since changes to network configuration are minimal. However, it is not too clear, on how network throughput (λ) will improve by the addition of more gateways. Broadly, this is the topic of study in this chapter.

More precisely, consider the case of N nodes arbitrarily distributed in a geographical area of $L \times L$ square-units as illustrated in Figure 3.1. We do not even know how the placement of a single gateway (or designating a node as a gateway as explained earlier) within such arbitrary network bears on the throughput (λ) and the "optimal" configuration of the network. Hence it is important that we study and understand the case of "optimally" placing a single gateway in the network prior to studying the case of optimally placing multiple gateways in the network. We hence begin this chapter by studying single gateway placement in networks by proposing heuristics to place a gateway at one of the node positions in the network. We will then study the case of multiple gateways. To describe the problem more precisely, lets take the case of placing 2 gateways in the network as illustrated in Figure 3.2. Clearly, the problem is to place two gateways in this arbitrary network so as to maximise the network throughput (λ). However, the issue is not only to find the optimal node-pair at which the 2 gateways need to be placed, but also to decide on

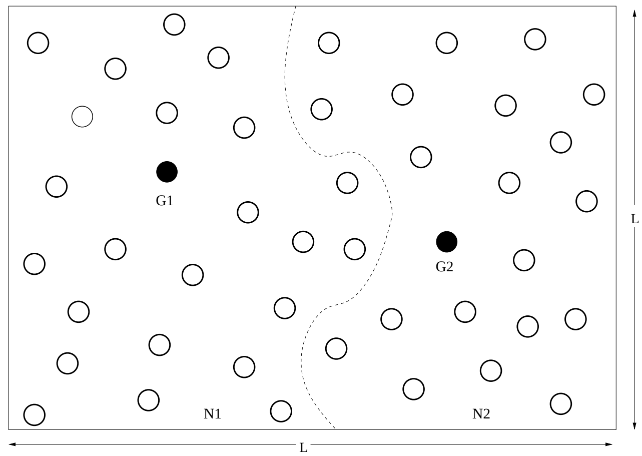


Figure 3.2: N nodes arbitrarily distributed within an $L \times L$ area.

the "sets" of nodes that associate with one of these 2 gateways. By association, we intend, that nodes forward their data-traffic to their "associated" gateway only. Node association is important since the number of nodes associated with a gateway significantly bears on the network throughput and hence it is important to designate the "optimal" set of nodes to be associated with a particular gateway. The problem now becomes more interesting, since we are seeking (i) gateway placements (ie., which node location must be designated as a gateway?) and (ii) node association (ie., which gateway should nodes in the network transmit/forward data to?) as well. In Figure 3.2, we have illustrated gateway placement and node association for the case of 2 gateways. $G1$ and $G2$ illustrate optimal gateway positions while nodes in sub-networks $N1$ and $N2$ illustrate node associations to gateways $G1$ and $G2$ respectively.

However solving these two problems depends on how this multi-gateway wireless mesh network is designed to operate as well. Clearly, in order to schedule sets of links (or sets of independent sets of links) as described in [9] in each of the constituent sub-networks (say $N1$ and $N2$) it is important that they do not use a single common frequency across the network since the resulting interference due to the use of one-common frequency may inhibit independent link-scheduling across the sub-networks. Hence each sub-network operate within non overlapping frequency bands. Subsequently, if a band-width B is allocated for the case of a single-gateway, $L \times L$ WMN, then each sub-network $N_i, i \in \mathcal{K}$ (where $\mathcal{K}$ is the set of gateways in the network and K the number of gateways in the network) within the total area $L \times L$ is now allocated a band-width B_i ($\{B_i | \sum_{\forall i \in \mathcal{K}} B_i = B\}$). Hence for the case of 2 gateway WMN illustrated in Figure 3.2 assuming $B_i = \frac{B}{2}, i = 1, 2$ and the number of nodes in sub-networks $N1$ and $N2$ as $\frac{N}{2}$, we need to compare throughput benchmarks associated with $(L \times L, N, B)$ with $(N1, \frac{N}{2}, \frac{B}{2})$. This network model is fairly straight-forward and we call it the *The Multiple Frequency Problem* or the *Split Bandwidth Problem* in this chapter.

The second option is to use the same bandwidth B for the 2 sub-networks. The use of a single bandwidth demands that operation of the two sub-networks are co-ordinated. This is the second and more complex network model and we call this as *The Common Frequency Problem* or the *Co-ordinated Schedule Problem*. A variant of this *Common Frequency Model* involves operating sub-networks independently, but using the same band-width throughout the network. Hence scheduling sets of links within each sub-network involves collisions due to interference from other sub-networks as well. We do not consider this network model however, since it is extremely difficult to evaluate the maximum network throughput (λ) in this case.

3.1 Related Work

The problem of gateway placement in wireless networks is an ongoing research problem. In [4] the authors pose the question of gateway placement under different wireless link models and propose algorithms for each of these models. Their algorithm iteratively selects a new gateway position from a given pre-determined set of gateway positions only if nodes associated with a new gateway have their demands (or QoS) satisfied. By assigning capacity to the wireless links and by using the max-min flow theorem [7], they are able to compute the capacity delivered by a new gateway position. In our study, we consider all nodes as probable gateway positions and with each iteration, we consider a subset of the nodes as gateways, discarding the others till our requirement of nominating K gateways are met. Further, assigning capacity to wireless links is a very hard problem, as explained in Chapter 1 and [9]. In [5], the researchers propose an algorithm that recursively computes the minimum weighted dominating set in determining gateway placements such that the QoS requirements of the users are satisfied. The authors in [3] propose a distributed clustering algorithm for determining gateway positions for ad-hoc networks. They consider node mobility unlike mesh network and base their decision on assigning nodes to gateways based on the amount of time a node has been already associated with the network. Similar to these works, we use a clustering approach, but base our clusters on creating regions of minimal interference. Since wireless transmission cannot guarantee an error probability of zero, and are based on an acceptable probability of error, we believe such an approach is more tuned to realistic network models. In creating clusters, we examine two approaches, *viz* (i) clustering minimal interference region within a network and then electing an optimal gateway position and (ii) electing an optimal gateway position in each iteration and updating this position within a cluster as the number of nodes added to the network increases.

Gateway placement problems have also been studied in the area of sensor networks. The authors in [2] formulate the gateway placement problem with the intent of reducing the energy and latency required by nodes to communicate with the gateway in power constrained sensor networks. Their algorithms recursively computes gateway positions by identifying competitive regions (areas of overlapping communication range) within the network. Sensor networks are often used to sample data in demanding and unsupervised environments. In [1], the authors propose a polynomial time algorithm that optimally places relay nodes (similar in role to gateways) with the intent of providing fault tolerant operations. Their clustering algorithm tries to determine the minimum number of gateways and their positions such that each sensor node in the network is able to communicate with at-least two relays.

3.2 Single Gateway Placement in WMN

In Section 1, we have described the 2-tiered organization of mesh networks. Accordingly, the organization of the back-haul tier controls how gateways access the internet and the organization of access-tier determines how nodes route their data-traffic to each of these gateways. In most wireless mesh networks, gateways are nodes themselves aggregating data from the rest of the nodes within the access tier. However, unlike the other nodes, data is no longer forwarded to other nodes, instead, this data-traffic is routed to the internet directly or by forwarding through a series of intermediate gateways. Similarly, for data destined for the nodes (in the access-tier) from the internet, gateways serve the role of data distribution points through which aggregated data reaching the gateways are subsequently distributed to the rest of the nodes through multiple hops. Effectively, gateways handle extremely large amounts of data-traffic. Further, the inherent organization of mesh networks where data is forwarded to the gateway through a series of hops implies a fully functional access-tier irrespective of the gateway location. It hence becomes important to answer if gateway placement within a network influences the network throughput (λ). If gateway, placement, is important, then it is only appropriate that schemes which designate a particular node within a network as an "optimal" gateway position are explored. These are some of the issues that are dealt in this section.

Fortunately, the computational tool derived from the optimization model in [9], provides us the means to accurately compute and compare the network throughput (λ) for various gateway positions in an N-node single-gateway WMN. By extensively using this tool for various node deployments, we have several interesting results on the behaviour of network throughput for varying gateway placements in an N-node network. We also use these results as insights in proposing a heuristic for "optimally" placing a single gateway in a network.

3.2.1 Gateway placement is important in WMN

Although the organization of mesh network implies that data can be forwarded to a gateway in any position from any node within the network, the placement of gateway does influence network throughput. From [9], however, we know that the maximum throughput of a single-gateway WMN is upper-bounded to $\frac{A}{N}$ (A, the maximum available data-rate in an N-node mesh network) clearly suggesting that gateway placement bears no impact on the maximum achievable network throughput. However this result no way specifies the transmit power at which the maximum throughput is achieved. Optimally placing the gateway within the network ensures that the maximum throughput is achieved for relatively less transmit power expenditure compared to other node positions within the

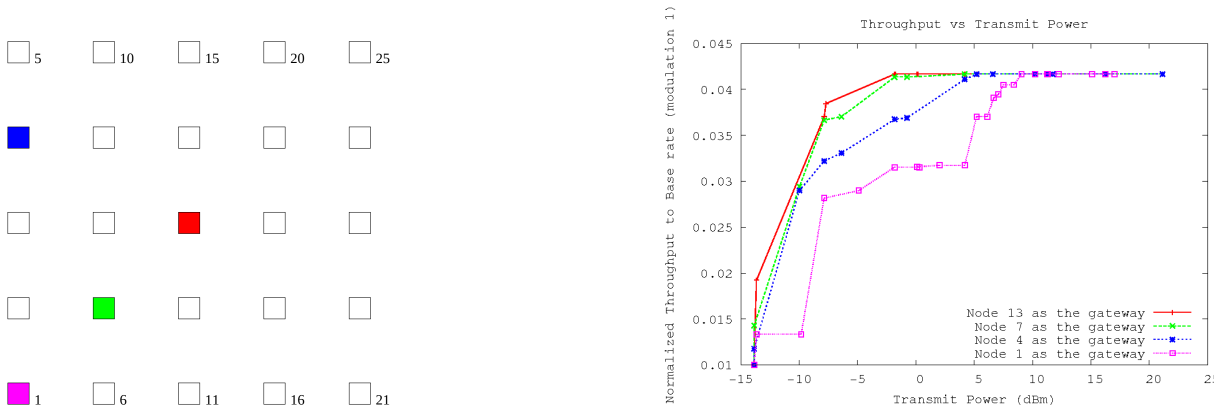


Figure 3.3: Variation of λ^* as a function of transmit power P (dBm) for various gateway positions indicated in a.

network. As an example, consider a 5×5 grid with 24 nodes and 1 gateway placed at various positions as indicated in Figure 3.3a. The variation of optimal throughput (λ^*) as a function of transmit power P is plotted in Figure 3.3b.

Clearly, gateway placed at node position 13 is “optimal” for two reasons: (i) compared to the rest of the gateway positions, gateway at node 13 reaches the maximum throughput of $\frac{A}{N}$ for less transmit power requirements than the other gateway positions and (ii) the throughput curve of this gateway position dominates the throughput curves of the other gateway positions indicating that at each discrete transmit power level, the gateway at node position 13 yields significantly better network throughput compared to other gateway position in the 5×5 grid. Clearly, gateway position within a mesh network does matter.

3.2.2 Gateway placement heuristic is necessary.

As illustrated in Figure 3.3b, the problem of single gateway placements can be posed and solved exactly. Clearly, by specifying, the “set” of modulation-coding schemes and the set of input powers available for known node locations, the optimization framework of [9] can be employed to accurately compute network throughput for varying gateway positions. However, this approach is computationally intensive and only gets worse if the “set” of modulation-coding scheme, the transmitter power levels available at each node and the set of nodes itself increases. Hence there is a need to explore heuristic schemes to place single gateway in networks.

For the case of regular networks (eg., complete grids, hex-topologies, sub-compact grids etc.) or irregular network based on grids (eg., grids with holes), where inter node separation is fixed and follows a specific pattern, operating at just enough power required for network connectivity (we call this power P_{min})and using a single modulation-coding scheme, we can prove the maximum throughput is given by

$$\lambda^* = \frac{1}{\sum_i h_{(i,j)}} \quad i \in \mathcal{N} \tag{3.1}$$

where $h_{(i,j)}$ is the minimum hop count for node $i, i \in \mathcal{N}$ to reach gateway at node j. Hence clearly, to maximise the network throughput λ, at the minimum power P_{min}, one should place the gateway at the node i that ensures

$$min \sum_i h_{(i,j)} \quad i,j \in \mathcal{N}, i \neq j \tag{3.2}$$

At this point, it is important that we observe results in Section 3.2.1 and Equation (3.2) closely. Clearly, if the optimal gateway position at P_{min} is "optimal" for all transmitter powers (refer Figure 3.3b), then a heuristic based on Equation (3.2) can be used for selecting a gateway positions for all transmit power greater than P_{min} as well. Since for the case of regular grid networks, the use of higher powers yields longer links, ensures that the minimum hop metric will still yield the gateway position identical to the gateway position at P_{min}. After a certain power level, other nodes in the network will also become "optimal" (or satisfy Equation (3.2)). This minimum hop metric forms our first heuristic $H1$.

In Section 3.2.1, we have used the example of a 5×5 grid to illustrate the case of gateway at node position 13 as being "optimal" since this gateway position yields the maximum throughput for least expenditure of transmitter power P. For the case of multi-hop mesh network, where multiple links can be scheduled simultaneously as explained in Section 1.1, computing the minimum power at which the maximum throughput is achieved is difficult. Instead, we use the following approach to circumvent this problem. The use of Single Hop links (all nodes can communicate with a gateway within a hop) (refer Figure

1.2b), in the network ensures maximum throughput $\frac{A}{n}$ is achieved [9]. Hence the optimal gateway position is the node that ensures the creation of single hop links for all the nodes with the minimum transmitter power. This can be used as a gateway selection strategy for designating a node in single-gateway WMNs.

Hence we select a node j as an "optimal" gateway position that ensures the transmitter power required to satisfy

$$P|\forall j \quad \left(\frac{d_l(i,j)}{d_o}\right)^{-\eta} \times P \geq \beta \quad i,j \in \mathcal{N} \;\; i \neq j \tag{3.3}$$

is minimum. $d_l(i,j)$ is the length of the link or the euclidean distance between nodes i and j and d_o is the cross-over distance. The SINR threshold β represents the SINR threshold of the highest modulation-coding scheme available in that network. We call this *Minimum Power* heuristic as $H2$.

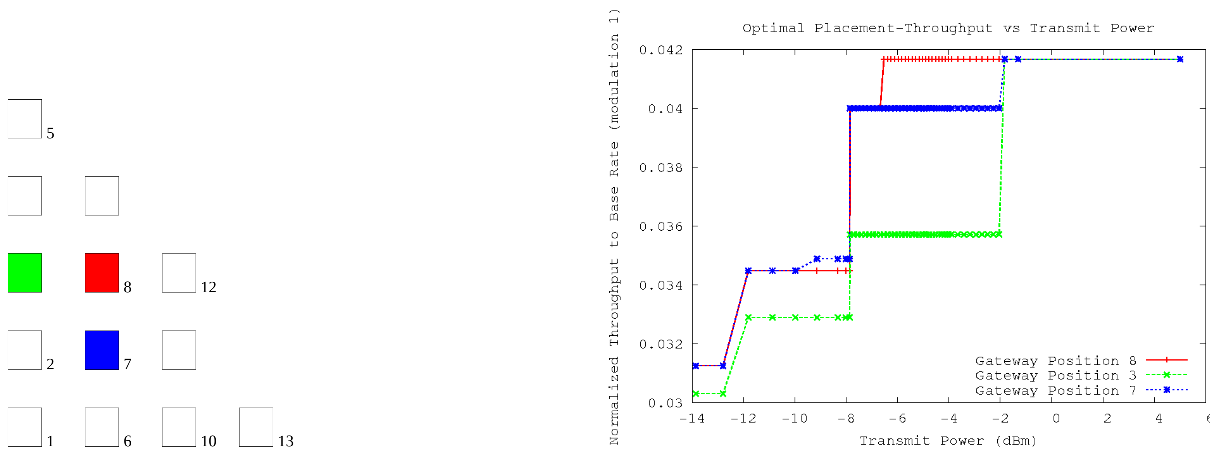
Let us evaluate how these two heuristics fare for the case of regular/irregular networks described above. We consider three cases to test for the "optimality" of these heuristics.

Regular and Complete Grid Networks

Consider the case of a regular 5×5 grid shown in Figure 3.3a. Clearly, as seen in Figure 3.3b, the throughput of the gateway at node-position 13 dominates gateways at other node positions. The results of using $H1$ on such a grid network is indicated in Table 3.1.

Power (in dBm)	Gateway Position
$-13.85 \leq P \leq 7.89$	13
$8.80 \leq P \leq 9.94$	$8, 12, 13, 14, 18$
$12.73 \leq P \leq 14.73$	$7-9, 11-15, 17-19$
15.55	$2-4, 6-20, 22-24$
≥ 15.75	All positions

Table 3.1: The *minimum-hop* heuristic $H1$ for the 5×5 grid yields gateway at node-position 13 as optimal for all powers. For very high powers, other nodes tend to become optimal due to longer link lengths.



(a) Sub-Compact Grid 1

(b) Throughput Curves

Figure 3.4: The variation of throughput (λ^*) for the case of the sub-compact grid shown in a., is illustrated in b.

Using $H2$ in these networks also yields gateway at node position 13 as optimal since this node requires a transmitter power of only 5.54 dBm compared to other node-positions to reach all other constituent nodes in the grid using single-hop links.

Regular but Incomplete or Sub-Compact Grids

Figure 3.4a illustrates an example of sub-compact grids. These grids are similar to regular grid networks since they follow a specific node placement pattern and fixed inter-node separation. To establish the throughput-curves, we follow the same methodology as explained in Section 3.2.1. We iterate over all possible gateway positions and choose 2 or 3 positions that yield the most optimal results relative to all other gateway positions for all powers. The variation of throughput (λ^*) as a function of transmit power P is plotted in Figure 3.4b. From the throughput curves, gateway at node-position 7 dominates for all discrete power levels barring a few points. Using Heuristic $H1$ yields two gateway positions 7 and 8 as being "optimal" for the input transmitter power range as indicated in Table 3.2.

Using the *Minimum Power* heuristic $H2$ yields the gateway at node-position 8 as being

Transmit Power (dBm)	Optimal Gateway Position
$-13.85 \leq P \leq -8.33$	7
$-7.56 \leq P \leq -2.37$	$7, 8$
$-1.82 \leq P \leq -0.27$	7
$0.22 \leq P \leq 4.09$	$7, 8$
$4.48 \leq P \leq 5.92$	$8, 12$
$6.27 \leq P \leq 8.2$	$2, 7, 8, 12$
$8.50 \leq P \leq 9.94$	$2, 3, 7, 8, 9, 11, 12$
14.09	All

Table 3.2: The *minimum-hop heuristic* $H1$ for the grid in Figure 3.4a illustrates two gateway positions 7 and 8 as being optimal.

optimal, since this position requires only 5.507 dBm for the creation of single-hop links to all nodes. Lets consider the case of another sub-compact Grid (refer Figure 3.5a). From the throughput curves, node-position at 7 dominates for all discrete power levels barring a few as indicated in Figure 3.5b. But, gateway at node-position 7 yields "optimal" results at power P_{min} and is the first node to reach the maximum throughput. Heuristic $H1$ however, yields two gateway positions 7 and 8 as being "optimal" for the input transmitter power range as illustrated in Table 3.3.

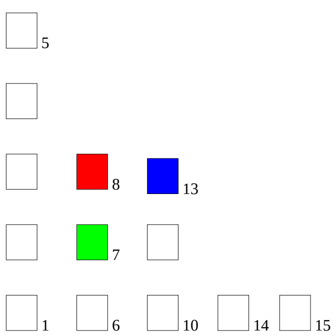
Using the *Minimum Power* heuristic $H2$ however, yields gateway at node-position 13 as being optimal, since this position requires only 5.507 dBm for the creation of single-hop links to all nodes. Clearly, as indicated in Figure 3.5b this gateway position is sub-optimal for all powers.

Irregular Grid Based Networks

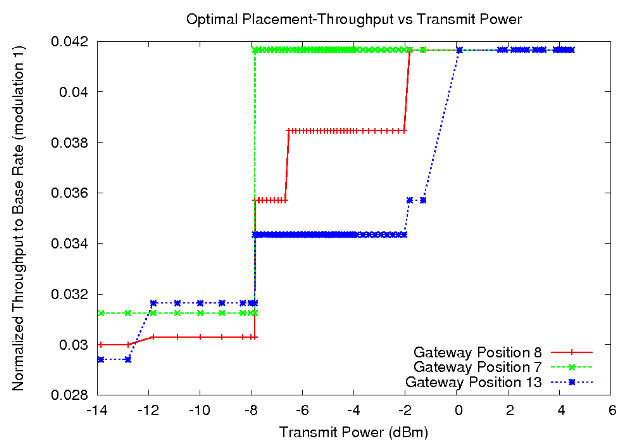
Figure 3.6a illustrates an example of an irregular grids network. These grids are similar to regular grid networks since they follow a specific node placement pattern with inter-node separation being constant throughout the network. However, unlike the regular grid networks, certain nodes in this grid are missing. To establish the throughput-curves, we follow the same methodology as explained in Section 3.2.1. We iterate over all possible

Transmit Power (dBm)	Gateway Position
$-13.85 \leq P \leq -8.33$	7
$-7.56 \leq P \leq -2.38$	7
$-1.82 \leq P \leq -0.27$	7
$0.22 \leq P \leq 3.70$	7,8,12
$4.48 \leq P \leq 7.9$	3,7
8.2	7,8,12,13
16.32	All

Table 3.3: The *minimum-hop heuristic* $H1$ for the grid in Figure 3.5a illustrates gateway positions 7 as being optimal.



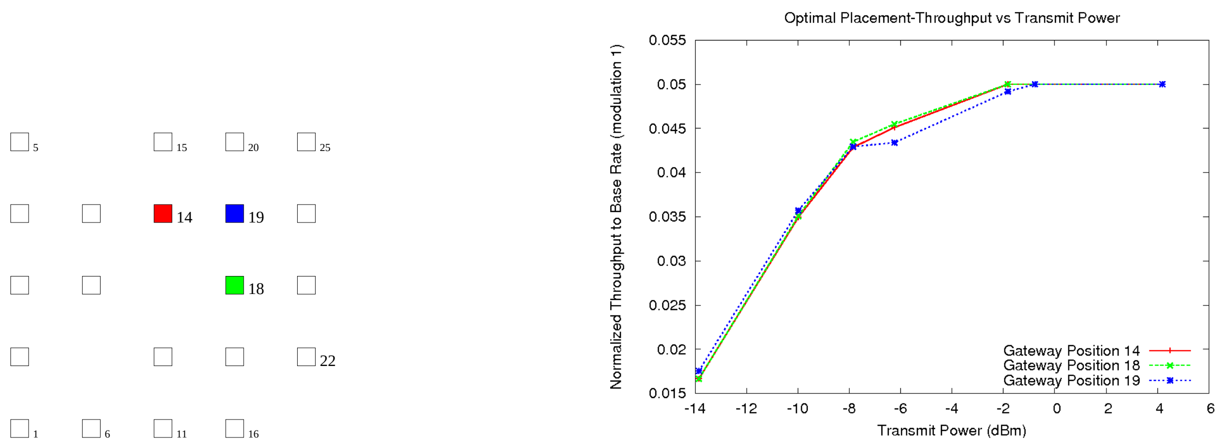
(a) Sub-Compact Grid 2



(b) Throughput Curves

Figure 3.5: The variation of throughput (λ^*) for the case of the sub-compact grid shown in a., is illustrated in b.

gateway positions and choose 2 or 3 positions that yield the most optimal results relative to all other gateway positions for all powers. The variation of throughput (λ^*) as a function of transmit power P is plotted in Figure 3.6b. From the throughput curves, gateway at node-positions $14, 18$ dominate for all discrete powers. Using Heuristic $H1$ yields gateway



(a) Irregular Grid

(b) Throughput Curves

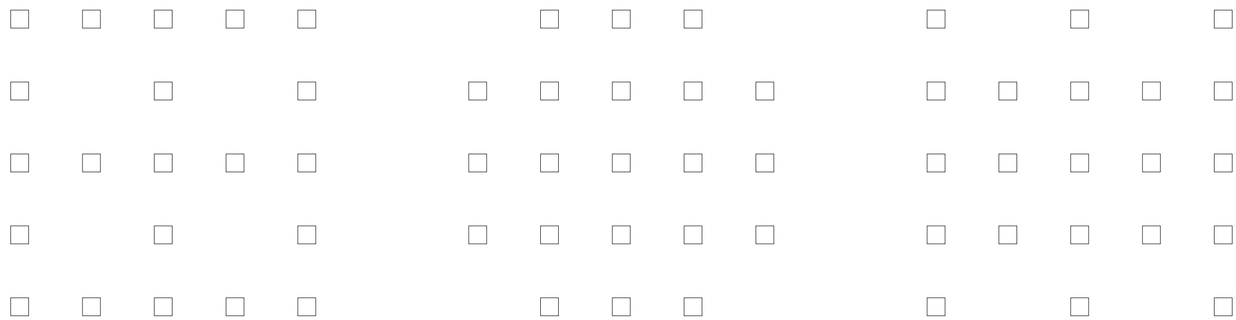
Figure 3.6: the variation of throughput (λ^*) for the case of an irregular grid shown in a., is illustrated in b.

position at 14 as being "optimal" for the input transmitter power range except at power P_{min} where gateway at node-position 19 is optimal, as illustrated in Table 3.4.

Transmit Power (dBm)	Gateway Position
$-13.86 \leq -8.33$	19
$-7.56 \leq -2.37$	$8, 12, 14, 18$
$-1.82 \leq -0.27$	$14, 18$
$0.22 \leq 3.70$	$8, 12, 14, 18$
$4.48 \leq 7.9$	$8, 12, 14, 24$
8.2	$8, 14$
16.32	All

Table 3.4: The *minimum-hop heuristic* $H1$ for the grid in Figure 3.6a illustrates multiple gateway positions $19, 18, 14$ as being optimal.

Using the *Minimum Power* heuristic $H2$ however, yields gateway at node-position $8, 12, 14, 18$ as being optimal, since these position require only 8.52 dBm for the creation



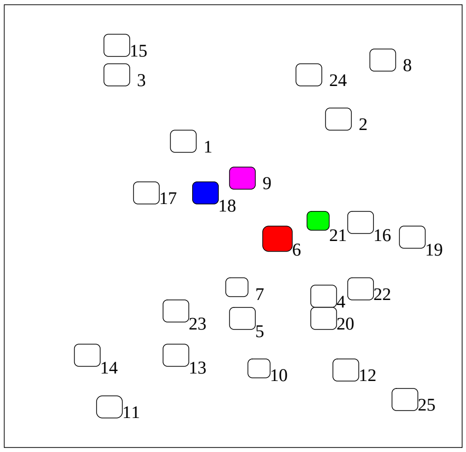
(a) Irregular grid 1 (b) Irregular Grid 2 (c) Irregular Grid 3

Figure 3.7: Illustrating several examples of symmetrical irregular grid networks

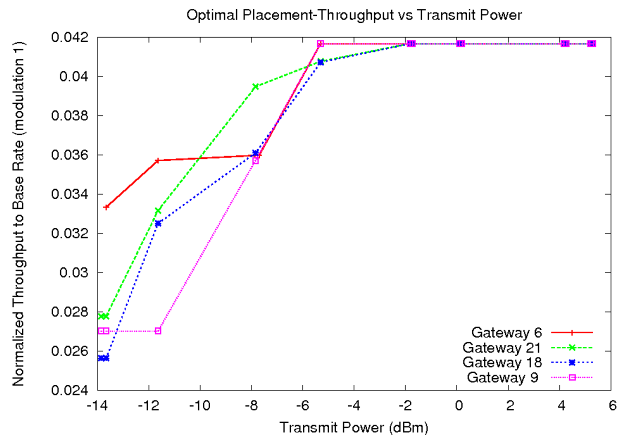
of single-hop links to all nodes.

At this stage it is interesting to evaluate these two heuristics based on some of the cases that we have illustrated above. As we have seen from these varying examples, there is no single heuristic $H1$ or $H2$ that can clearly designate a node-position as an "optimal" gateway location. The success of these two heuristics are largely dependent on the node organization. For the case of regular and complete grid networks, both heuristics yield optimal results and this gateway position dominates the throughput over all other gateway position as seen in Figure 3.3b. For all other networks, sub-compact grid networks and irregular networks based on grids, the "optimality" of the gateway position as computed using heuristic $H1$ or $H2$ is largely dependent on the node organization. For networks in which the constituent nodes exhibit "symmetry" in their organization as illustrated in Figures 3.7, it is expected that, a gateway at a specific node-position will dominate other node-positions. Hence for these cases, gateway positions nominated by $H1$ for the case of power P_{min} and gateway position nominated by $H2$ for the case of power P_{max} is identical. Hence both heuristics can be used to nominate gateways in the network. However, cases of "symmetrical" networks that violate this property can also be conjured.

However for networks that do not offer any symmetry (eg: Figure 3.6a), no single heuristic yields optimal results for all input power ranges. Depending on the node organization in these types of networks, certain gateway positions may or may not dominate other gateway positions for all input power ranges. Clearly if $H1$ and $H2$ yield identical



(a) Arbitrary Network



(b) Throughput Curves

Figure 3.8: The variation of throughput (λ^*) for the case of an arbitrary network in a., is illustrated in b.

results in these networks, then the gateway position is easily determined. However, if these two heuristics nominate different gateways, then $H1$ can be used to nominate a gateway position in these networks by selecting the node that satisfies the minimum-hop metric, maximum number of times.

Our experience with these two metrics clearly show the difficulty involved in nominating gateways for networks that are neither *regular* and *complete* nor *irregular* but *symmetrical*. This problem becomes more complicated in the case of arbitrarily distributed nodes where inter-node separation is no longer constant. Clearly, *minimum-hop* metric cannot be used in these scenarios. Further, as we have already explained in Section 1.1, our network model incorporates multiple modulation-coding schemes as well. Clearly, any metric must accommodate these as well in computing the gateway position in the network. Such a metric is discussed in the next Section.

A SINR based link metric

In an effort to incorporate these physical layer parameters like multiple modulation-coding schemes and circumvent the problems associated with using *minimum hop* metric on arbitrary networks, we propose the following link-metric:

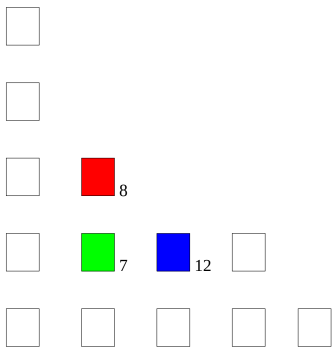
$$w_l = \frac{1}{\gamma_l \times c_l} \tag{3.4}$$

where γ_l is given by the LHS of Equation (1.1). A link metric based on SINR also has the added advantage of modelling the geographical conditions of the network. An obstruction in the network easily results in low SINR and hence we are able to incorporate the physical environment, network layout, node-density etc., into our metric as well. Further, by using this metric, it is clear that robust links (links with higher SINR values), have lower weights relative to less-robust links. Hence path weights computed using this metric corresponds to low-interfering routes between two specific nodes. Hence within a particular network, any node which results in the lowest average SINR-weight computed from this node to every other node becomes a favourable candidate to be considered as a possible gateway position. Specifically, gateway positioned at node i that ensures

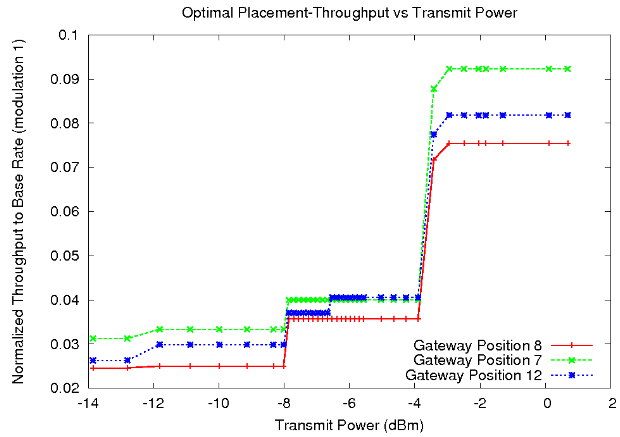
$$min \left\{ \sum_{\forall j \in \mathcal{N}, i \neq j} \gamma_{(i,j)} \right\} \quad i, j \in \mathcal{N} \tag{3.5}$$

is considered as an optimal gateway position; where $\gamma_{(i,j)}$ is the total SINR weight computed between nodes i and j using the link metric w_l. We call this heuristic $H3$. To evaluate this heuristic, we consider two networks (i) a 24-node arbitrary network and (ii) a Regular and sub-compact grid network with 2 modulation-coding schemes. Consider the arbitrary network in Figure 3.8. The use of $H3$ yields node-position 6 as being optimal. From the throughput curves in Figure 3.8b there is no single node that is optimal over the entire transmitter power range, but gateway at position 6 is optimal for most of the powers barring a few and the attainment of maximum throughput by gateway at node-position 6, follows no other node.

Consider the case of the sub-compact grid as illustrated in Figure 3.9a where the constituent nodes can operate with a choice of two modulation-coding schemes. The throughput curves are indicated in Figure 3.9b. Clearly gateway at node-position 7 dominates the rest of the gateways over all transmit power levels. By using the heuristic $H3$, we also arrive at the same result of nominating gateway at node-position 7 as the optimal gateway position.



(a) Arbitrary Network



(b) Throughput Curves

Figure 3.9: The variation of throughput (λ^*) for the case of an arbitrary network in a., is illustrated in b.

These heuristics $H1$, $H2$ and $H3$ can also be used to place gateways within sub-networks (or clusters). These algorithms are explained in Sections 3.3.1, 3.3.2 and 3.4.

3.3 The Common Frequency Problem

Under this network model, all wireless nodes and designated gateways operate within a single bandwidth. The model is depicted in Figure 3.3, where the use of uni-color links is intended to show that all nodes operate within a single bandwidth and employ a common frequency to communicate. Nodes however are multi-colored (red and blue in this case) to designate that nodes only forward their data-traffic to the gateway that they are associated to.

We do not attempt to solve this problem exactly as in the case of single-gateway networks [9]. Instead, we propose two heuristics based on the SINR link metric (refer Section 3.2.2) to optimally place K gateways in an N-node network and designate sets of nodes that are associated with each of these K gateways. Further, we extend the optimization model of [9] to accurately compute network throughput and the configuration for the case

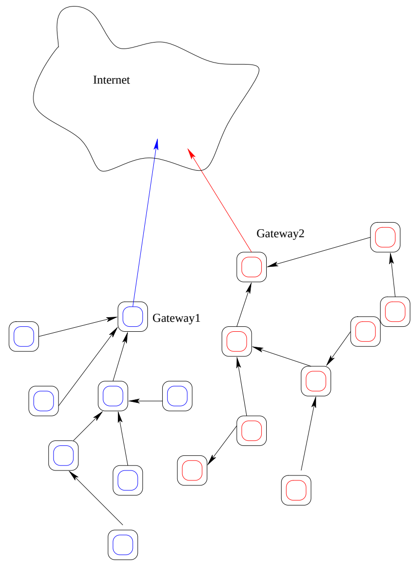


Figure 3.10: *Common Frequency* Network Model: Network model for arbitrarily placed nodes and multiple gateways, all operating at the same frequency

of K-known gateway positions under the condition that nodes forward data traffic to their associated gateways only. Such an optimization model yields two interesting results: (i) It computes the maximum throughput achievable for the case of K gateways in an N-node network. (ii) Node association to gateways is also specified as part of the complete "optimal" configuration of the network. These results can then be used as a benchmark to evaluate our own node-association results which are part of the heuristics.

We use the same notations barring a few described in Section 1.1. Unless we restate definitions for variables used in this model, all notations revert back to the same definition used in [9]. As explained earlier, our aim is to maximise the data transmitted to a particular destination through K gateways. The data transfer requirements is still specified in terms of flows, denoting a source-destination pair, but unlike in [9], flows here are specific to nodes destined to a particular gateway only and hence we modify the definition of the flow variable to include this change. Under this assumption, we restate the set of flows as denoted by $\mathcal{F}$. The cardinality of this set denoted by $M = N \times K$. Each flow $f \in \mathcal{F}$ is now associated with a node-gateway pair $(i, j), i \in \mathcal{N}, j \in \mathcal{K}$. Let x_l^{ij} represent the flow variable associated with a flow $f \in \mathcal{F}$ on link l. For an associated node-gateway pair, λ_i denotes the flow rate. The binary variable ρ_{ij} ensures that nodes source or sink data specific to one particular gateway only.

Under this assumption, we can state the optimization problem as

$$max\ \lambda \tag{3.6}$$

$$\sum_{l \in \mathcal{L}_k^O} x_l^{ij} - \sum_{l \in \mathcal{L}_k^I} x_l^{ij} = \begin{cases} 0 & k \neq i, j \\ \lambda_i \rho_{ij} & k = i \\ -\lambda_i \rho_{ij} & k = j \end{cases} \qquad k = 1 \ldots N + K \tag{3.7}$$

$$\sum_{i,j} x_l^{ij} \leq c_l \sum_{m \in I_l} \alpha_m \quad l = 1 \ldots L \tag{3.8}$$

$$\sum_{m \in \mathcal{I}} \alpha_m = 1, \tag{3.9}$$

$$\alpha_m \geq 0 \tag{3.10}$$

$$\begin{aligned} &\sum_j \rho_{ij} = 1, \qquad i = 1 \ldots N \\ &\rho_{ij} \in \{0, 1\}, \quad i = 1 \ldots N, j = 1 \ldots K \\ &0 \leq \lambda \leq \lambda_i, \qquad\qquad i = 1 \ldots N \end{aligned} \tag{3.11}$$

Clearly from this optimization model, our objective (3.6) is to maximise network throughput (λ) under the following constraints: Constraint 3.7 is the flow conservation constraint which specifies that unless nodes aligned to a particular gateway sources or sinks any data, the total data flow through the node $i, i \in \mathcal{N}$ is zero. To force this condition we use the binary variable ρ_{ij} specified for every node $i, i \in \mathcal{N}$ and gateway $j, j \in \mathcal{K}$. Constraint 3.8 specifies the capacity conservation constraint. This constraint limits the amount of flow handled by each link l to be within or equal to the capacity of the link specified by the data-rate c_l and the link activation schedule $\alpha_m, m \in \mathcal{I}$. Constraint 3.9 indicates the summation of ρ_{ij} for a node-gateway pair is unity thus forcing all data to be forwarded by node i also associated with the same gateway j. λ_i is the flow variable for each node i that needs to be maximised.

We describe the proposed algorithms for the common frequency problem in detail in the subsequent sections. We propose two algorithms to select gateway positions in mesh networks. In the first algorithm, we recursively choose gateway positions with each iteration or with a set of nodes added, thereby growing the size of the clusters and terminate the algorithm when there are no more nodes to be added in the network. In the second algorithm, however, we select gateway position by identifying the required number of clusters and then selecting the best gateway position in each of these clusters.

In all algorithms, our input parameters are the set of N nodes that constitute a network topology, the K gateways that need to be positioned and the metric w_l that assigns a weight to every possible link as determined by the transmit power and modulation-coding scheme. Our output are a set of nodes, the cardinality of this set being equal to the number of gateways required to be positioned and the list of nodes that are assigned to each of these gateways. Specifically, abstracting the network as a graph model; given a directed graph $G = (V, E)$ representing a network, where the vertices V are representative of the nodes and E, the directed edges the algorithms partitions V into subsets $\{V_1, V_2, \ldots V_K\}$, where K is the number of gateways to be positioned as part of the input specification and $\bigcup_{i=1}^{K} V_i = V$, such that each V_i forms a connected subgraph of G. We describe the algorithms.

3.3.1 Algorithm 1: Clustering by Leader Election

1. The algorithm starts with all nodes declaring themselves as gateways. In this algorithm, the term gateways and cluster-head are used inter-changingly.

2. All links in the communications network have an SINR-based weight metric assigned to them. Each of the cluster-heads compare their link-weights with the adjacent nodes. If a node, say A, has a lesser link weight than its neighbouring node B, then node B resigns its cluster-head status and associates with node A. Note: The design of our link metric ensures that links with relatively lower weight are more robust than links with higher weights as explained in Section 3.2.2.

   In retaining or resigning their cluster-heads status, certain nodes might enter an infinite recursive loop. Since a cluster-head which has a node associated with it, might resign its status when compared to another node with better link-weight and assign itself to the other node. This might result in a recursive loop with some nodes resigning their cluster-head status or being nominated again as a cluster-head depending on the link weights. To circumvent this problem, a node loses its cluster-head only if no nodes are associated with it already. Since we pick nodes in a random fashion and compare link weights, this problem gets evenly distributed.

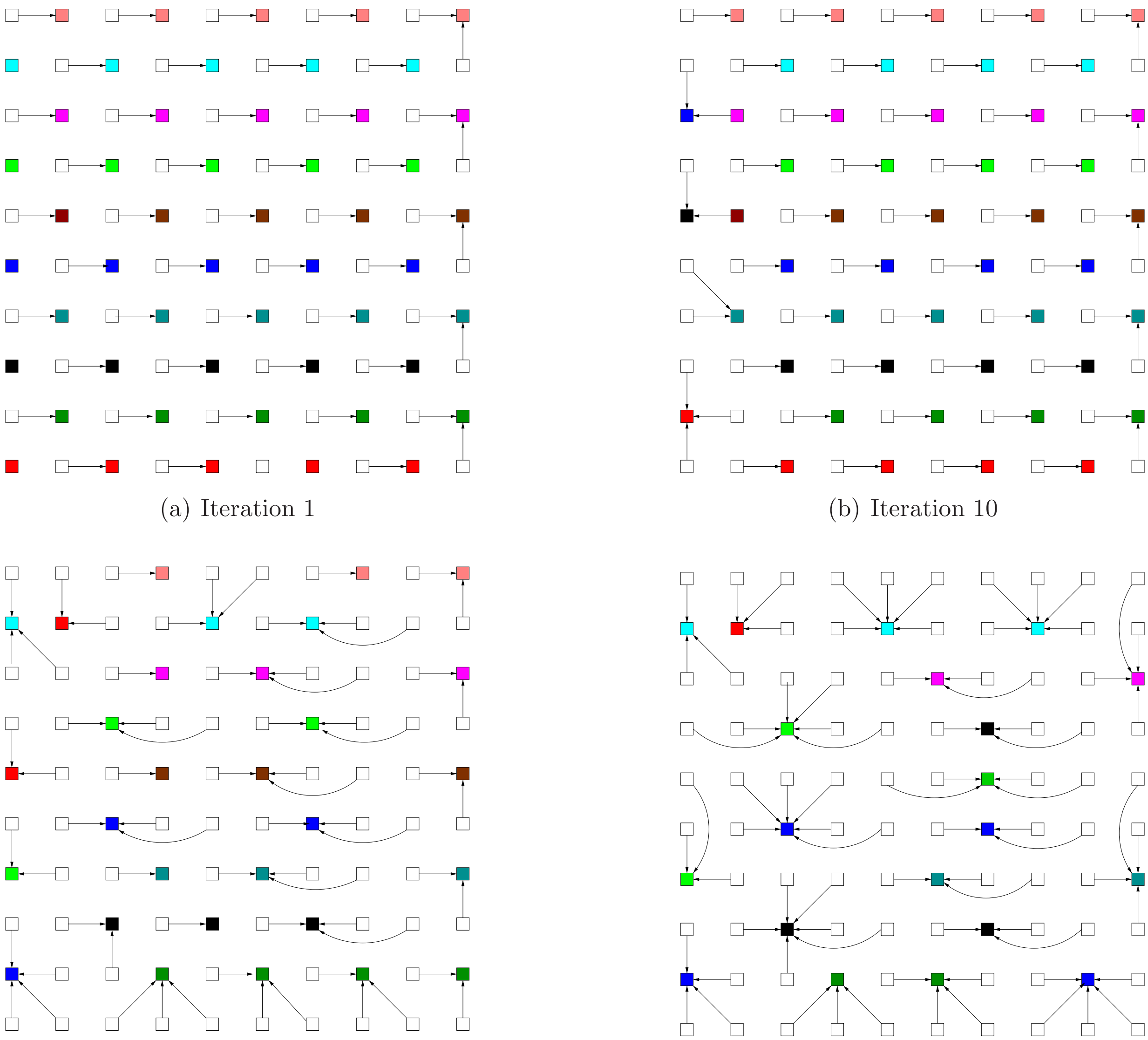
Similar action is repeated throughout the network and at the end of the first iteration we have two sets of nodes. Nodes which still have retained their cluster-head status due to a better link weight compared to its neighbouring node and nodes which have resigned their cluster-head status and associated themselves with the node which has a better link metric. The cluster-head and the nodes associated are all within one-hop reachability.

3. With the previous step completed, we now compute the number of clusters that exist by determining nodes which have still retained their cluster-head status. If this number is more than the number of gateways to be positioned, we go to the next step, else we skip to step 6.

4. In this step, we identify the cluster with the smallest number of nodes associated with the constituent cluster-head. In case there exists multiple clusters with the smallest number of nodes associated, then we pick any one of the clusters in a random fashion. We break this selected cluster by forcing the cluster-head to resign its status and re-assigning all associated nodes including the cluster-head to other clusters. To enable re-association of these nodes, for each node we compute the shortest SINR path to a cluster-head. Such computation can be carried out using a distributed algorithm such as the Dijkstra's Algorithm. To enable additive link weights, we take the *log* of the computed SINR weights and use them in the Dijkstra's algorithm.

5. At this step, we have assigned nodes to cluster-heads which are multi-hop distant. Once the re-association is carried out, we re-position/re-align the cluster-head to reflect the growth in the cluster. In section 3.2, we have explained in detail, the schemes adopted to nominate a cluster-head within a cluster.

6. Unlike step 4, we have reached here, since more number of clusters are required than what is available after the termination of step 2. Unlike step 4, we identify the cluster with the largest number of nodes associated, force resignation of the cluster-head and



(a) Iteration 1

(b) Iteration 10

(c) Iteration 20

(d) Iteration 30

Figure 3.11: Algorithm Growth for a 10 $\times$ 10 grid: Gateway positions after iteration a. 1, b. 10, c. 20, c. 30 Note: Some cluster-heads (shown by a coloured filled square have no nodes associated with them

repeat step 2, under the condition that the former cluster-head will not be allowed to regain cluster-head status. With this, several new smaller clusters will be formed. We repeat this step till the number of gateways equals the number of clusters and associating nodes of the lost cluster with other appropriate clusters based on the least cost (path-weight) path to a cluster-head.

7. At the end of the step 5, we have reduced the total number of clusters by 1. The number of clusters are now compared with the total number of clusters required. If the required number of clusters (corresponding to the number of gateways) are less, we recursively repeat steps 4 and 5. After each iteration, we check if the number of cluster-heads equals K.

8. This algorithm terminates when the number of clusters are equal to the number of gateways required. At the termination, we have K clusters or sub-networks with a node in each cluster serving as a cluster-head or a gateway.

Correctness of the Cluster

The algorithm starts by declaring all nodes as cluster-heads (*gateways* and terminates by designating K nodes as cluster-heads, with each cluster-head also specifying *its* set of nodes. As described in Section 3.3.1, a node may leave a cluster for two reasons: (i) Its link-weight is more compared to the link-weight of the other node. (ii) Certain clusters are terminated and corresponding nodes forced to join their neighbouring clusters.

Simulation and Results

This algorithms has been simulated for a 10×10 grid network for placing 10, 8, 6 and 4 gateways respectively. Each of the grids considered have a inter-node separation of $8m$. For the simulation, we have considered single-rate links, although as evident from the link-metric (refer Section 3.2.2) accommodating multi-rate links are also quite possible. Also, a transmit power of -13.84 dBm on each links corresponds to a transmission range of 8.01 m. The SINR-threshold is fixed at 10 dB. Although we have indicated algorithm growth at power P_{min} corresponding to the power required for minimum node connectivity our

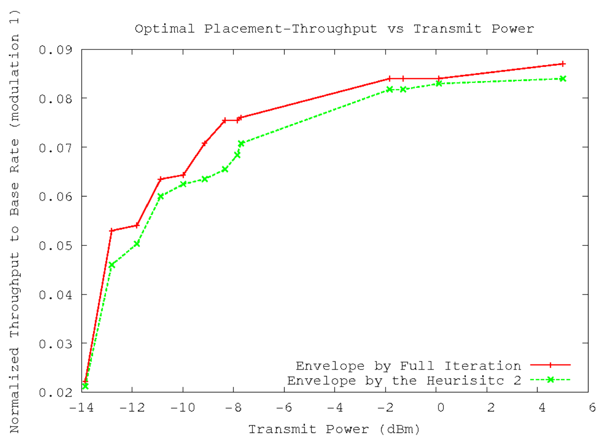


Figure 3.12: Variation of λ as a function of transmit power for the case of a 5×5 grid illustrating the performance of the “Clustering by Leader Election” algorithm

algorithm works well for other power ranges as well. The results of using this algorithm is illustrated in Figure 3.13(a-d).

Figure 3.12 illustrates the results of using *Algorithm 1* on a 5×5 grid to designate 2 nodes as gateways ($K = 2$). To establish the upper bound (red curve) we choose the following strategy: since we have two elect 2 gateways for the range of powers considered, we iterate over all node pairs and select the best gateway pair (the highest throughput offered) for each transmit power. We compute these results by basing our computational tool on the optimization framework defined in Section 3.6. Using our heuristic, we determine the gateway pair for each transmitter power level, compute its maximum throughput, derive an envelope of these results and plot them in Figure 3.12. Compared to the upper-bound, our heuristic yields sub-optimal results. This is expected since we are not solving the problem exactly. However, note that the worst gateway-placement occurs at -7.85 dBm and is within 10% of the upper-bound result. The gateway positions computed through iterations and the gateway positions obtained by using this algorithm is indicated in Table 3.6

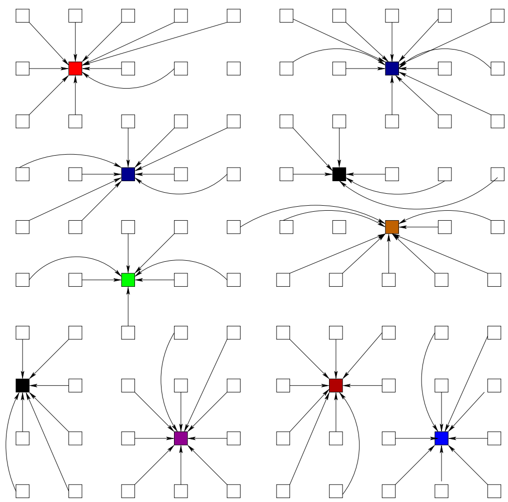
Power (in dBm)	Gateway Position (Iteration)	Gateway Positions (Algorithm 1)
-13.845699	8,17	8,22
-12.802818	8,17	7,22
-11.811008	3,23	2,17
-10.872779	3,18	7,19
-9.982637	2,24	8,22
-9.135891	2,24	8,21
-8.328507	2, 19	7,19
-7.854278	3,23	8,22
-7.702942	3,23	7,19
-1.824347	3, 23	7,19
-1.300642	3,23	7,19
0.112180	3,23	7,19
5.010006	3,23	7,19

Table 3.5: Comparing Gateway positions obtained by iterating over all node-pairs and by using the Algorithm 1 for corresponding transmitter power levels.

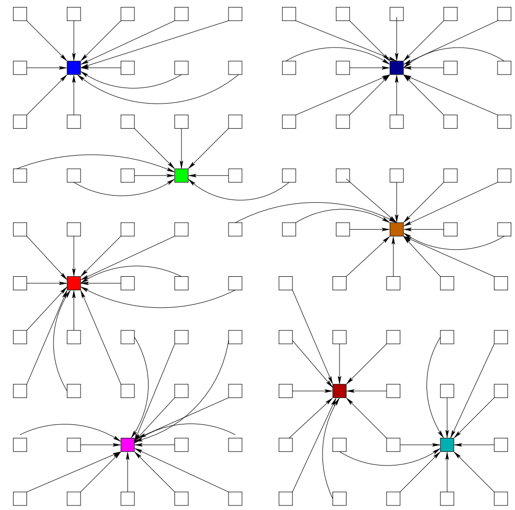
3.3.2 Algorithm 2: Clustering by Maximal SINR weights

In this section, we describe an algorithm, that first forms K clusters corresponding to K gateways and then elects a cluster-head for each of these K clusters. The description of the algorithm follows:

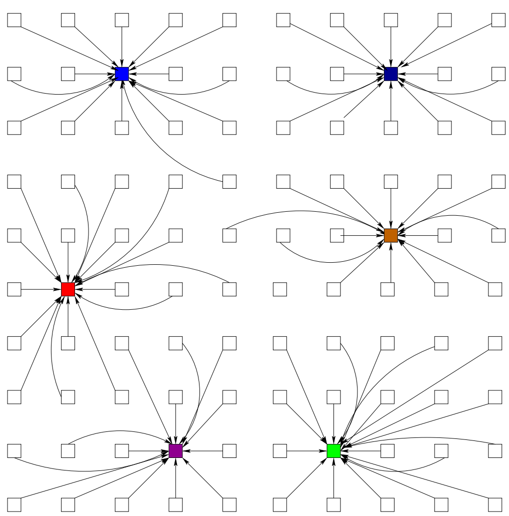
1. We have already indicated assignment of link weights based on the metric. In order to facilitate computing robust paths, we use a distributed algorithm like Dijkstra's Algorithm. As already indicated in the previous algorithm, to enable additive links, we compute the natural logarithm of each of the SINR weights and use these *modified* weights throughout this algorithm. At the start of the algorithm, we already have computed the path length from every node in the network to every other node. In computing the shortest SINR-distance, we also compute for each node, the number of nodes that are in the periphery of the network. By *peripheral nodes*, we simply



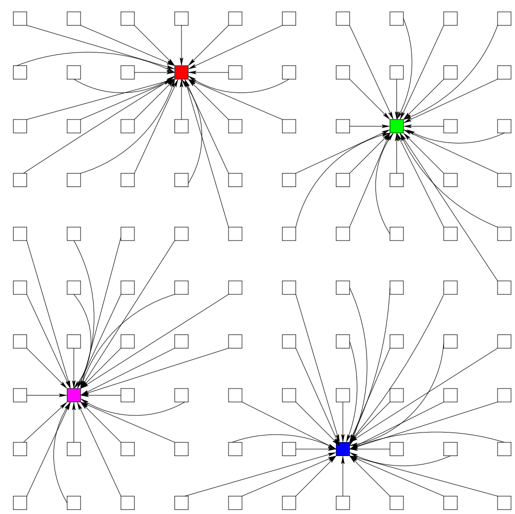
(a) 10 Gateways



(b) 8 Gateways



(c) 6 Gateways



(d) 4 Gateways

Figure 3.13: Common Frequency Problem, 10×10 grid: Gateway positions for the case of a. 10 gateways b. 8 Gateways c. 6 Gateways d. 4 Gateways in a 100 node network

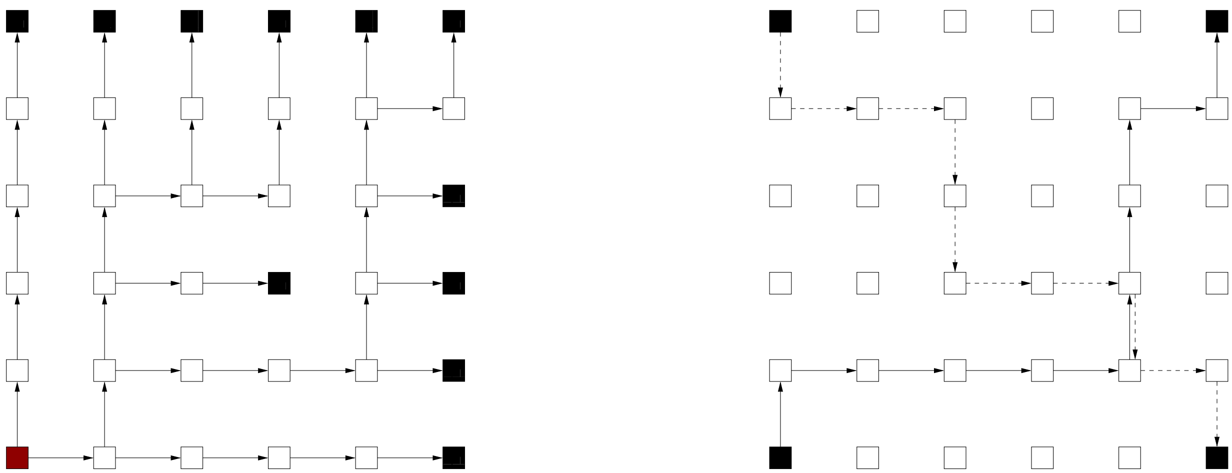


Figure 3.14: a. Nodes at the periphery (grey patterned squares) of a 6×6 grid network as seen from Node 1 computed using the Dijkstra Algorithm. b. Selecting nodes for the case of $K = 2$. The longest paths (in this figure, the solid and dotted lines) or paths of maximum SINR weight are chosen. Nodes 1 and 31 are initially selected for iteration 1.

consider nodes that are not used by Dijkstra's Algorithm to reach other nodes. In Figure 3.14a, we indicate a 6×6 grid and based on the SINR metric, the reachability from node 1 to other nodes is indicated. As illustrated in Figure 3.14a, certain nodes (grey patterned squares) are not used to reach other nodes and these nodes are considered as the *peripheral nodes*. We compute such nodes for all nodes in the network.

2. In the previous step, we have identified the *peripheral nodes*. Reachability to these nodes represents the longest SINR-distance as computed by Dijkstra's Algorithm. We sort these paths in ascending order and pick the K greatest paths. Now in view of the fact that a path can be abstracted as one link that spans the entire path with two end nodes and we are picking K paths, this implies that one node in each path must be discarded to facilitate K clusters. Any one of the two nodes can be discarded, since as will be explained later, we will be examining all maximum SINR paths and the nodes which are discarded will be considered later. To illustrate this,

consider Figure 3.14b, where two maximum SINR paths (corresponding to $K = 2$) have been selected for a 6×6 grid network. These paths correspond to Nodes $1 \rightarrow 36$ and $6 \rightarrow 31$. In the first iteration, we pick nodes $1, 31$ corresponding to paths $1 \rightarrow 36$ and $6 \rightarrow 31$ discarding nodes 6 and 36.

3. We will use the term *sector-head* to identify the nodes selected (for eg, nodes $1, 31$) in the previous step. Using these *sector-heads* we start associating the rest of the nodes in the communication network to any of these sector-heads depending on the shortest SINR path.

4. The previous step continues untill all nodes are associated to any one of the K sector-heads. In the actual implementation however, we associate nodes to sector-heads by continuously increasing the hop count till all nodes are mapped. By hop count, we intend, that in the first iteration, nodes which are within 1-hop distance from any of the sector-heads are checked for sector-heads with the shortest SINR-weight and then assigned to a particular sector-head. There might be cases, when the hop count might be higher for a certain node, but its SINR-distance to a sector head is relatively small compared to the SINR distance from another sector-head. We take care of this problem, by not associating the node, untill the particular hop-count is reached. Such a direction is formulated from a purely implementation perspective, but the algorithm itself was designed oblivious to the hop-count.

5. At the end of the previous step, we have all nodes associated to sector-heads. At this point we choose the next set of K paths, select K nodes of these K paths by discarding a node from each of these paths and iterate from step 3 to step 4. These iterations are performed untill all combinations of the peripheral paths have been extinguished.

6. The loop terminates when there are no longer any paths to choose from. At this step, we examine sector-heads and the number of nodes associated with them and choose the sector-heads that have equitable number of nodes associated to each of the sector-heads.

In Figures 3.23 (a-d) , we have illustrated the growth of the algorithm for the case of

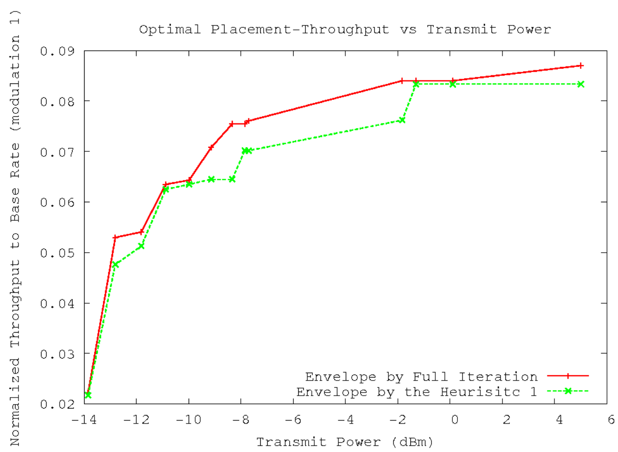


Figure 3.15: Variation of λ as a function of transmit power for the case of a 5×5 grid illustrating the performance of the "Clustering by Maximal SINR Weights" algorithm

4 gateways in a 10×10 grid network. Note: as compared to the previous algorithm in 3.3.1, there is no progression of the gateway placement, in the sense, that in the previous algorithm, every iteration resulted in a decreasing number of gateways positioned optimally till the limit of K was reached. In this algorithm however, we need to run the algorithm independently for changing K requirement.

7. Placing the gateway in each of these sectors follows the same principle as defined in section 3.3.1 and is explained in 3.2.

3.3.3 Simulation and Results

Figure 3.3.2 illustrates the results of using *Algorithm 1* on a 5×5 grid to designate 2 nodes as gateways ($K = 2$). Computing the upper-bound is explained in the previous section. As expected, this heuristic also yields sub-optimal results. But compared to *Algorithm 1*, the results are much closer to the upper-bound. In-fact the lowest throughput results at -7.85 dBm as well and is within 8% of the upper-bound. The yield of this algorithm compared to *Algorithm 1* over the rest of the input power range shows marked improvement. However, this algorithm becomes time-intensive with increased K and N since the number of nodes to iterate across increases quite rapidly.

Power (in dBm)	Gateway Position (Iteration)	Gateway Positions (Algorithm 1)
-13.845699	8,17	8,18
-12.802818	8,17	8,19
-11.811008	3,23	8,18
-10.872779	3,18	8,18
-9.982637	2,24	8,18
-9.135891	2,24	8,18
-8.328507	2, 19	8,18
-7.854278	3,23	8,18
-7.702942	3,23	8,17
-1.824347	3, 23	8,17
-1.300642	3,23	8,18
0.112180	3,23	8,18
5.010006	3,23	8,18

Table 3.6: Comparing Gateway positions obtained by iterating over all node-pairs and by using the Algorithm 2 for corresponding transmitter power levels.

3.4 The Multiple Frequency Problem

Figure 3.3b indicates the *Multiple Frequency* network model. The dotted and the dashed links denote links operating at unique frequencies.

Similar to the previous optimization model, we use the same notations as described in Section 1.1 unless redefined here. The network data transfer requirements are specified in terms of flows. However, under the multiple frequency network model, where a set of links and nodes operate with a unique frequency, the destination is no longer the gateway but a “hypothetical-sink” called the “internet” to which data must be forwarded. Hence although, we still consider a flow as a source-destination pair, the destination however is

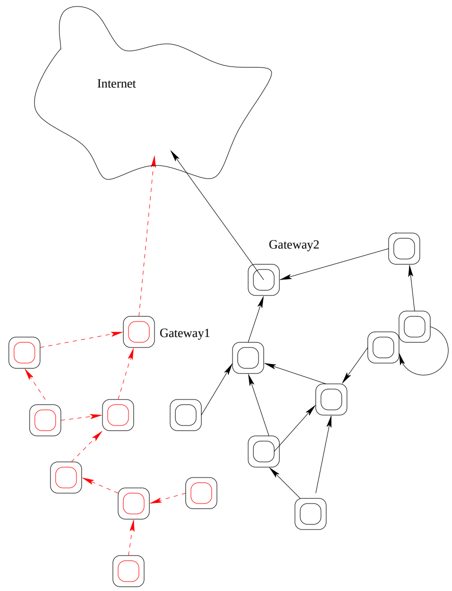


Figure 3.16: *Multiple Frequency Network Model*: Network model for arbitrarily placed nodes and multiple gateways with gateway and nodes associated with them operating using a unique frequency.

unspecified since we consider the "hypothetical sink" as the destination. Hence we define the flow specific to the nodes of a unique frequency only. The set of flows is denoted by $\mathcal{F}$ and its cardinality denoted by F. For each node $i, i \in \mathcal{N}$ let x^i_{lf} represent the flow variable associated with a flow $f \in \mathcal{F}$ on link l. λ_i denotes the flow rate for each node. The binary variable δ_{ilf} ensures that the capacity assigned to a link l for a specific flow f is zero unless destined to a particular gateway.

Under this assumption, we can state the optimization problem as

$$
\begin{aligned}
& max\ \lambda && && (3.12)\\
& \textstyle\sum_{l \in \mathcal{L}_k^O} x_{lf}^i - \sum_{l \in \mathcal{L}_k^I} x_{lf}^i = \begin{cases} 0 & k \neq i \\ \lambda_i & k = i \end{cases} && k = 1 \ldots K && (3.13)\\
& \textstyle\sum_i x_{lf}^i \leq \delta_{ilf} c_l \sum_{m \in I_l} \alpha_m, && l = 1 \ldots L && (3.14)\\
& \textstyle\sum_{m \in \mathcal{I}} \alpha_m = 1, && && (3.15)\\
& \alpha_m \geq 0 && && (3.16)\\
& \textstyle\sum_{lf} \delta_{ilf} = 1, && i = 1 \ldots N && \\
& \delta_{ilf} \in \{0, 1\}, && i = 1 \ldots N,\ lf = 1 \ldots K && (3.17)\\
& 0 \leq \lambda \leq \lambda_i, && i = 1 \ldots N &&
\end{aligned}
$$

Clearly from this optimization model, our objective (3.12) is to maximise network throughput (λ) under the following constraints: Constraint 3.13 is the flow conservation constraint which specifies that unless nodes aligned to a particular gateway sources or sinks any data, the total data flow through the node $i, i \in \mathcal{N}$ is zero. Constraint 3.14 specifies the capacity conservation constraint. Unlike the *Common Frequency* model, where we put the binary test variable ρ_{ij} to ensure that a flow is handled only by a particular node-gateway combination, here, we specify the binary test variable δ_{ilf} on the capacity of the link. Essentially, unless a link l carries data using a particular frequency, we null the link by assigning the capacity of the link l to zero ($\delta_{ilf} = 0$). Otherwise, this constraint limits the amount of flow handled by each link l to be within or equal to the capacity of the link specified by the data-rate c_l and the link activation schedule $\alpha_m, m \in \mathcal{I}$. Constraint 3.15 indicates the summation of δ_{ilf} for a node is unity thus forcing all data to be forwarded by node i. λ_i is the flow variable for each node i that needs to be maximised.

Algorithm: Leader Election by Updating SINR weights

Algorithms 1 and 2, can be very well used in the *Multiple Frequency Problem* as well, since these algorithms only create clusters by aggregating nodes based on low-interference. However any algorithm for the *Multiple Frequency Problem* must factor in the added advantage gained by using multiple frequency within the network by each gateway and its associated nodes. Such an approach makes nodes communicating with different frequencies completely oblivious to each other, in the sense that nodes operating with different frequencies no longer interfere with each others communication and transmissions can co-exist while both these nodes operate simultaneously. We modify *Algorithm 1* to reflect this advantage. We explain the modified algorithm:

1. Once *Algorithm 1* terminates, we have K clusters formed and a cluster-head within each cluster selected. At this point, we retain the cluster-head position and cancel all node associations to these cluster-heads.

2. At the completion of the previous step, we have identified the gateway positions but we do not have any nodes associated with these gateways. This algorithm starts off, by identifying nodes which are within one-hop distance from each of the K cluster-head and associating a node with a cluster-head if its link weight is less than the link-weight to other cluster-heads similar to the procedure defined in *Algorithm 1*. At the end of this step, we have three types of nodes. Nodes designated as cluster-heads, nodes assigned to specific cluster-heads and unassigned-nodes.

3. We recompute the SINR weights of the nodes as explained: For all links that have neighbouring nodes associated with different cluster-heads, we assign a very large weight (or $infinity$) in an attempt to discourage Dijkstra's Algorithm from using these links to compute a path from an uncovered node to a cluster-head. The use of multiple frequency makes such links redundant. Next, for all links that have a node associated with a particular cluster-head and the other node unassigned, we compute SINR by considering the nodes that have similar cluster-head associations or nodes which are unassigned, since only these contribute to the interference. Finally, for links that have two neighbouring unassigned nodes, we recompute the link weight as detailed in 3.2.2.

4. Node association is then executed in the same fashion as detailed in 4. After a node has been associated with a particular cluster, we update SINR weights by following the procedure in 3 and iterate over steps 4 and 3.

The algorithm growth hasnt been illustrated since it follows the *Algorithm 1.* The results however has been indicated in Figure 3.17

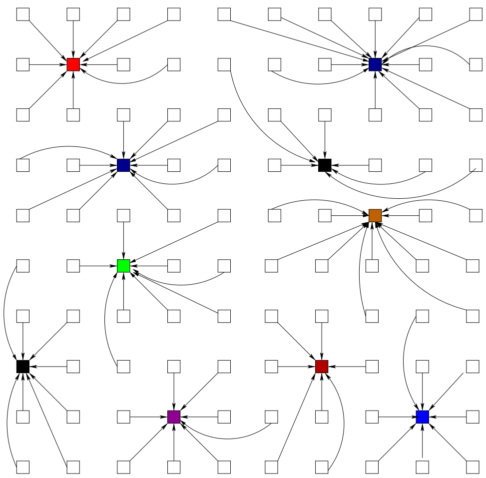
Simulation and Results

This algorithms have been simulated for a 10×10 grid network for placing 10, 8, 6 and 4 gateways respectively. Each of the grids considered have a inter-node separation of $8m$. For the simulation, we have considered single-rate links, although as evident from the link-metric (3.2.2) accommodating multi-rate links are also quite possible. Also, a transmit power of -13.85 dBm on each links corresponds to a transmission range of 8.01 m. The SINR-threshold is fixed at 10 dB.

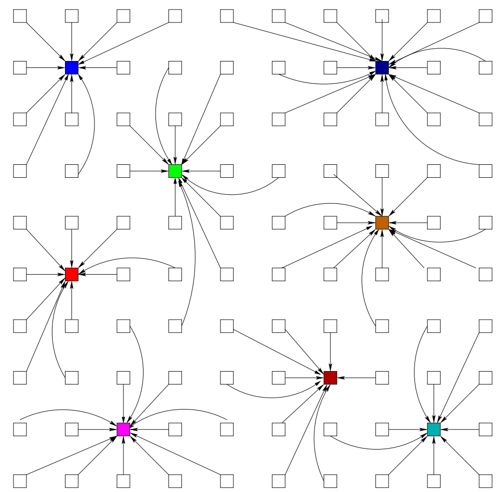
Establishing the upper-bound for the case *Multiple Frequency* network model is fairly difficult since the gateway position within a cluster, the number of nodes within a cluster and the configuration of the cluster itself bear direct influence on the behaviour of network throughput. Although from our analysis in Section 3.5, we have identified some thumb-rules that makes identifying the "optimal" cluster size and the "optimal" gateway position within a cluster easier; establishing the "optimal" cluster configuration (the node distribution) is fairly difficult. However for the case of small networks, eg: 5×5 grids and for the case of a small K (eg. $K = 2$), permutations of cluster configurations to consider is fairly minimal and brute force approach can be employed to find the right cluster configuration for each transmit power. This information along with our thumb rules explained earlier can then be used to get an insight in establishing the upper-bound. This upper-bound can then be used for testing the optimality of *Algorithm 3.* Using the brute-force approach the sub-network configuration illustrated in Figure 3.18a with the gateway at node-position 8 is found to be "optimal". Using this as our upper-bound we plot the results of our algorithm computed using the framework in Section 3.4.

3.5 Algorithm Requirements

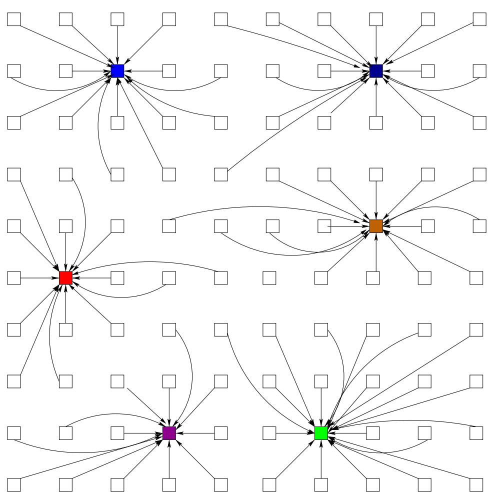
Our algorithms defined in the previous sections are motivated by several insights obtained by using the computational tool in [9]. In this section, we list some of the insights and relevant results,



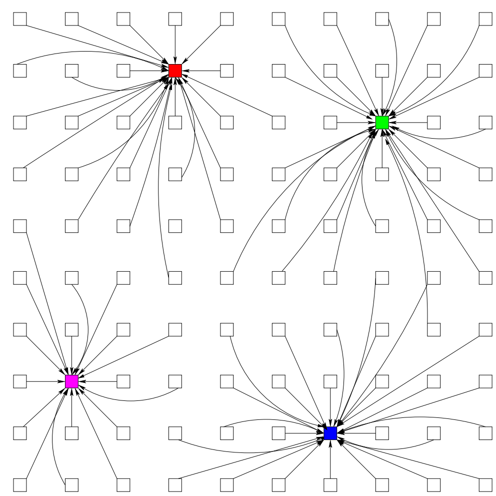
(a) 10 Gateways



(b) 8 Gateways

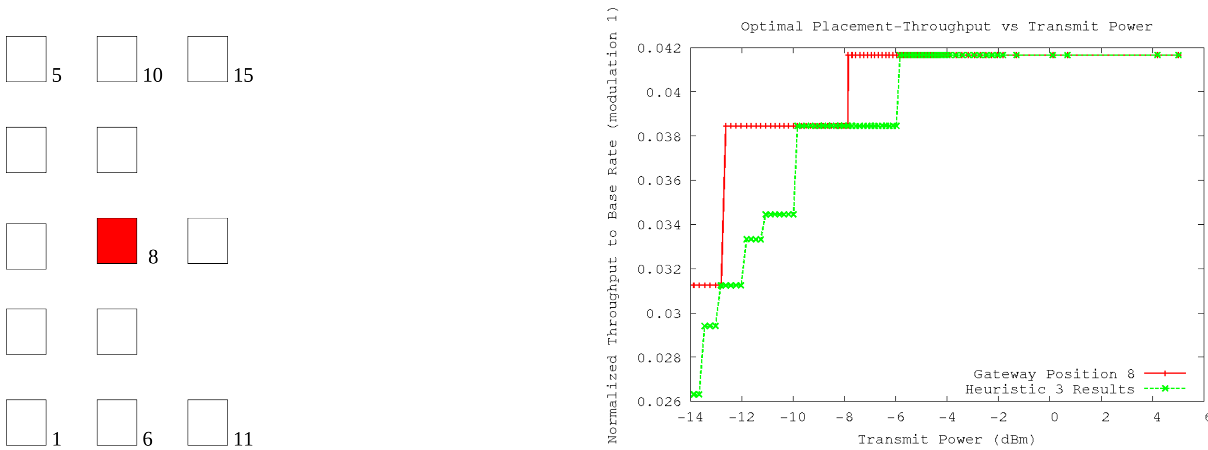


(c) 6 Gateways



(d) 4 Gateways

Figure 3.17: Multiple Frequency Problem:10 $\times$ 10 grid: Gateway positions for the case of a. 10 gateways b. 8 Gateways c. 6 Gateways d. 4 Gateways in a 100 node network



(a) Optimal Division

(b) Throughput Curves

Figure 3.18: The variation of throughput (λ^*) for the case of the sub-network illustrated in a. is plotted in b. Results of using Algorithm 3 are also plotted in b.

Clustering Based Approach

In [8], the authors indicate that the capacity λ available at each node to source a packet is upper-bounded by the relation

$$\lambda < \frac{\frac{C}{n}}{\frac{L}{r}}, \tag{3.18}$$

where C is the total one-hop capacity of the network, n, the number of nodes in the network, L the expected physical path length from the source to destination and r is the fixed radio transmission range. Equation (3.18) clearly indicates that in multi hop networks, where traffic is sequenced over a set of hops, the available capacity at each node to transmit a packet falls off with increasing path length which only underscores the idea that relay-load in multi-hop networks must be minimised in order to maximise network throughput. The need for clustering also arises from a communication cost perspective. By keeping traffic localised to a particular cluster, communication costs which involves maintaining routing tables or costs imposed by the overlying network protocol can also be significantly minimised. Moreover, when the number of nodes increases or decreases

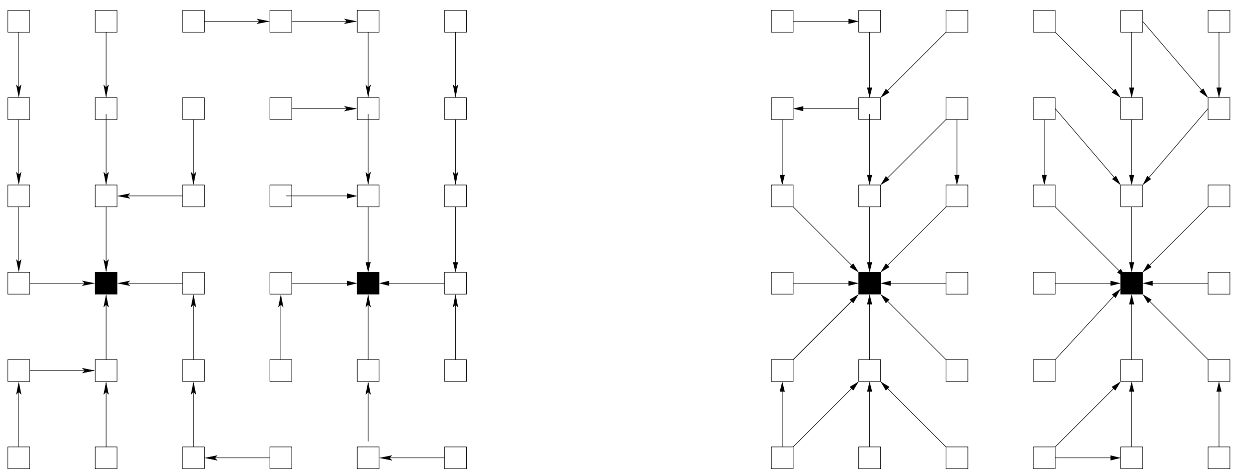


Figure 3.19: Optimal Routing for a $6\times 6 grid$ corresponding to transmit powers a. -13.8456 dBm and b. -1.72695 dBm

(the network scales up or down), ensuring that traffic is localised to a cluster implies any network changes affects a particular cluster only and the rest of the network is isolated from these performance degradation. The computational tool in [9] lends credence on the optimality of using *clustering-based* algorithms in designing high throughput multi-gateway WMNs. Figures 3.19a and 3.19b illustrate the optimal routing for a dual-gateway WMN with node 9 and 27 considered as gateways, for two values of transmit powers, -13.845 dBm and -1.726 dBm respectively. Clearly, *clustering* is in-place, since the gateways have *divided* the 6×6 grid into two sub-networks and each of these gateways serve a specific set of nodes only. In other words, the network traffic is being localised around gateways.

All these suggest that optimal performance can be obtained if the network is composed of sub-networks or clusters, each with a set of nodes and a cluster-head. The cluster-head performs the same role as a gateway.

Multiple gateway networks with equitable number of nodes associated with each gateway have the maximum throughput

Clearly, our clustering based approach explained earlier signifies division of the network in terms of clusters of gateways and *their associated* nodes. Specifying the throughput of the overall network hence involves ensuring that every sub-network or cluster meets the *throughput* specification. Under such circumstances, it is clear that this throughput specification suffers due to the existence of large clusters, since they result in reduced throughput (by [9], it is clear that the throughput of single-gateway WMN scales as $O(\frac{1}{n})$). Considering that the overall network has K-clusters or K-sub-networks and each cluster has $(n_i | 1 \leq i \leq K)$ nodes, the upper-bound on the throughput can be maximised if all clusters have equal node assignments $(n_i = n_k | i \neq k, i, k \in (1, K))$.

To illustrate this example, we consider a 6×6 grid and designate pairs of nodes as gateways. Table 3.7 indicates gateway-pairs and the number of nodes associated with each gateways and their throughput all computed using the computational tool from [9]. From Table 3.7, it is evident that gateway positions which enable equitable association of nodes offer higher throughputs compared to the other gateway positions.

]

$GatewayPairs$	$Throughput$	$Nodes/Gateway$
8,19	0.00934	19,15
10,13	0.01086	21,13
9,16	0.01041	23,11
3,33	0.01111	17,17
2,29	0.01177	17,17

Table 3.7: Gateway Pairs and the corresponding throughput

Multiple gateway networks with equitable number of nodes associated with each gateway have their throughput maximised when the inter-gateway separation is maximised

One of the characteristics of multi-hop networks is the progressive aggregation of data-traffic in the intermediate nodes as data is forwarded from source to the destination. The nodes in the immediate vicinity of the gateways (*the last hop nodes*) are critical since data aggregated over the entire network is forwarded to these nodes for transmission to the gateways. It is hence important that the last-hop links are scheduled more often and for longer durations to reduce the relay load which is invariably high in these links. Such a measure improves network throughput. Our network model stipulates that we explicitly compute sets of links that can be simultaneously scheduled with each other ("independent sets" of links). As explained in Section 1.1, the scheduler then chooses an optimal configuration of these "independent sets" of links to maximise network throughput. Our model of computing "independent sets" of links and our desire to schedule last hop links as much as possible clearly indicates the infeasibility of positioning gateways close to each other. Such a step will ensure that: (i) the last-hop links of different gateways cannot form an "independent set", since activation of one last-hop link will be at the cost of another last-hop link. The proximity of gateways to each other ensures that the resulting interference will be too high for links of both gateways to co-exist. Network throughput is hence reduced since last-hop links which bottle-neck network throughput suffer further due to interference of another last-hop link associated with another gateway.

In Figure 3.20, we illustrate two 6×6 grid with nodes 16 and 22 designated as gateways (Figure 3.20a) and nodes 8 and 29 designated as gateways (Figure 3.20b). In Figure 3.20a, the solid line represents a scheduled last-hop link and the proximity of the two gateways ensures that corresponding last-hop links (broken lines) corresponding to the other gateway will not be scheduled. However in Figure 3.20b, last-hop links corresponding to both gateways can be scheduled simultaneously and hence throughput improves. Using the computational tool from [9], we are able to quantify the improvement in network throughput for gateway positions illustrated in Figures 3.20 *a* and *b*. As expected, the network throughput of Figure 3.20b, shows significant improvement over Figure 3.20a.

In Table 3.8, we illustrate this for several gateway placements. Each gateway pair indi-

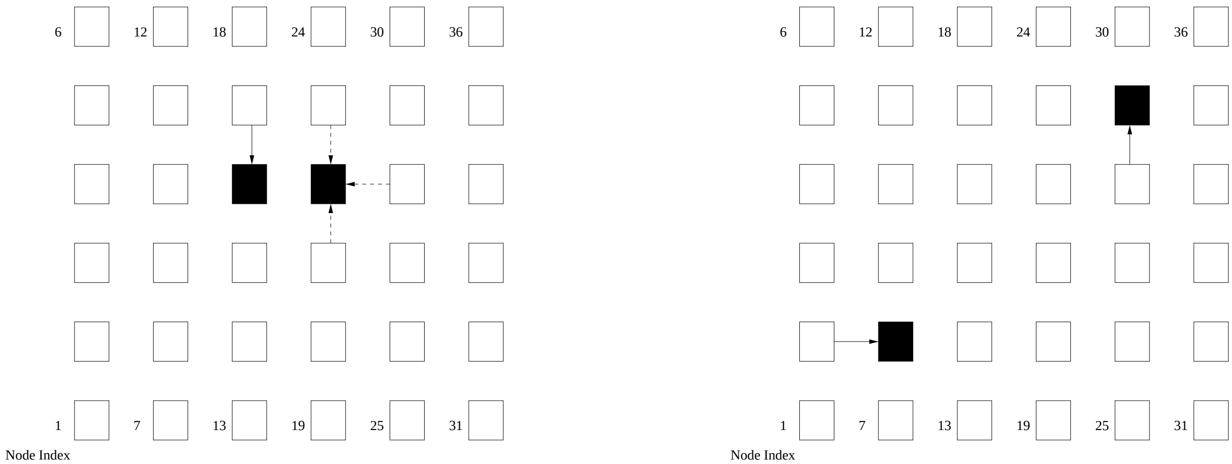


Figure 3.20: 6×6 : 2-gateway network

$Gateway Pairs$	$Throughput$	$Nodes/Gateway$
8,29	0.00609	17,17
16,22	0.00555	17,17
1,36	0.00909	17,17
3,33	0.01111	17,17
2,29	0.01177	17,17

Table 3.8: Gateway Pairs with equal node association

cated in Column 1 results in equitable node division (Column 3). Column 2 illustrates the throughput computed using [9]. Several observations are in order. First, as explained, note that the throughput achieved by gateway pairs 8 and 29 (Figure 3.20b is much higher than the throughput achieved by gateway pairs 16 and 22 (Figure 3.20a. Second, ensuring that gateways are as further apart from each other also serves to degrade network throughput as observed from gateway pairs $1, 36$ compared to gateway pairs $3, 33$ and $2, 29$. This is because gateways 1 and 36 are no longer in the logical center of their respective clusters and hence throughput degradations are expected. Third, note that although gateway pairs $1, 36$ contribute to sub-optimal network performance, their throughput however shows marked improvement compared to gateway pairs $8, 29$ and $16, 22$. Such behaviour gives insight on the influence of last-hop links on the throughput of the network.

3.6 Common vs Multiple Frequency: A Note on Performance

We set out to study the problem of gateway placement in WMNs by modelling two different networks. Although we based these models on how users are affected in the event of a gateway failure, advantages in countering noise and interference and the operational ease were other factors that were also considered in formulating these network models. While attempting to address the problem of gateway placement, we made some interesting observations on the behaviour of these networks. We delve in to these observations in this section.

3.6.1 Spatial Reuse Gains

As explained earlier, our *multiple frequency* model was based on dividing network band-width into K sectors, where K is the number of gateways to be placed. Each gateway and its associated nodes operate with a unique frequency which is $\frac{1}{K}$ part of the total band-width. Since noise in the network is modelled as *additive white Gaussian* normalized over the entire band-width, any division in network band-width leads to division in noise power as well. This reduction in noise power increases the overall spatial reuse. Spatial reuse in the network is determined by the transmitter signal power and the cumulative effect of noise and interference along with the modulation-coding scheme employed. Mathematically restating equation 1.3 from Section 1.1, we have

$$\mathcal{I} = \left\{ x : \frac{G_{ll}P_l}{N_0 + \sum_{l',l\neq l'} G_{l'l}P_{l'}x_{l'}} > \beta_l x_l, \forall l \in \mathcal{L} \right\} \tag{3.19}$$

It is evident that any reduction in noise power from N_0 to $\frac{N_0}{K}$ contributes significantly to increasing the spatial reuse. However, it must be noted that the bound on the “maximum

Figure 3.21: Spatial Reuse plot as a function of the Transmit Power P for 3 cases: Common Frequency Network Model, Multiple Frequency Network Model and a Single Gateway Network, shown for the case of a 5×5 grid. Note that using Multiple frequency Model increases the Spatial reuse substantially.

independent set" or MAXISET explained in Section 1.1 must be independently computed for each of the K cluster within the network. The total "maximum independent set" of the *full* network then is the summation of the "maximum independent set" of each of the K clusters. To illustrate, we consider a 5×5 grid with 23 nodes and 2 gateways. Figure 3.21 indicates the spatial reuse gain for the *Multiple Frequency* model. The MAXISET for the *multiple frequency* model is given by the addition of the MAXISET for two clusters that constitute the 5×5 grid. However, spatial gains associated with the *multiple frequency* model are absent in the *Common Frequency* network model. Hence, in terms of spatial reuse, modelling multi-gateway WMNs to employ multiple frequency is clearly advantageous.

3.6.2 Clustering

In proposing algorithms for solving the gateway selection problem in multi-rate multi-power WMNs, researchers must contend with two important issues: (i) Clustering (ii) Optimality

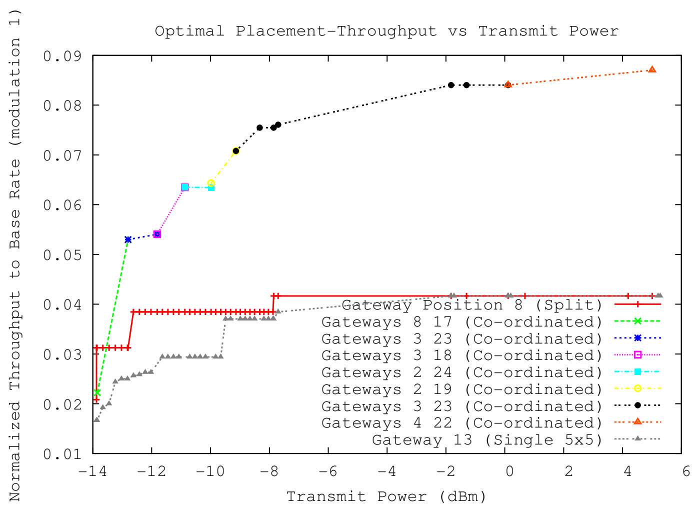


Figure 3.22: Variation of λ with the Transmit Power P for 3 cases: Common Frequency Network Model, Multiple Frequency Network Model and a Single Gateway Network, shown for the case of a 5×5 grid.

of gateways. The problem is not in identifying the clusters and gateway positions, but in ensuring that clusters and gateways are optimal for all transmitter powers and modulation-coding schemes employed by the WMNs. Owing to the complex inter-dependence between routing, scheduling, signal power, modulation-coding scheme etc, proposing a strategy for identifying the *right* cluster and the *right* gateway is fraught with difficulties and makes gateway selection in WMNs particularly hard.

Using the computational tool of [9], we have illustrated the problem for the case of 5×5 grid with 2 gateways. To establish the upper-bound in throughput, we have iterated over all possible gateway pairs for a set of discrete power levels (powers that enable links to establish basic node connectivity to links that span the entire network are considered in this range) and choose the best gateway pair for each discrete power level. The variation in throughput as a function of transmitter power is plotted in Figure 3.22. In this case however, we have used a single modulation-coding scheme, although similar results can be expected if the network supports multi-rate modulation scheme as well. From the figure, it is clear that no single gateway pair is optimal over the entire range of transmitter power level. The changing gateway positions that are optimal for each chosen power also exacerbates the problem of optimally identifying clusters within the network.

3.6.3 Throughput Gains

The *multiple frequency* network model leads to "cleaner" networks since division of network bandwidth leads to reduced noise and contributes to increased spatial reuse. However the bandwidth division adversely affects the networks throughput. Each modulation-coding scheme has an associated data-rate c_l which signifies the number of bits transmitted per symbol. This data-rate is dependent on the band-width as given by the Shannons Channel Capacity equation:

$$C = W log\left(1 + \frac{SNR}{W}\right) \tag{3.20}$$

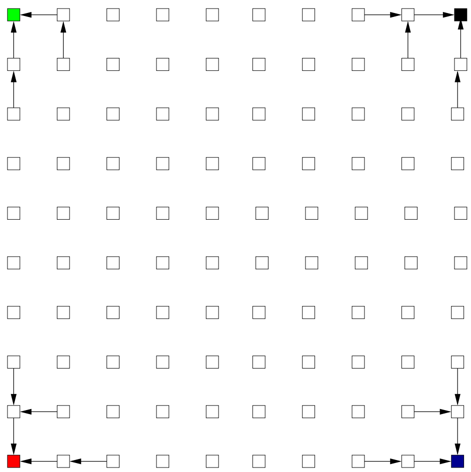
It is clear that dividing the bandwidth W by K, reduces the data-rate by K as well for each modulation-coding scheme employed in the network. Hence, unlike the *common frequency* network model, where installing more gateways increases network capacity, the *multiple frequency* network model actually hampers network throughput. This is also evident for the case of a 5×5 grid with 2 gateways. The variation of network throughput as a function of the transmit power is indicated in Figure 3.22. It is evident that for the case of the common frequency model, the maximum throughput scales linearly withe addition of gateways. The maximum throughput of a single-gateway WMN with 24 nodes and 1 gateway is 0.041667, while the maximum throughput for the case of 2-gateway 5×5 grid with 23 nodes is 0.08756. Note: In our computational tool, certain nodes split traffic to both gateways and hence the maximum throughput is greater than $\frac{K}{N}$

Hence between the two network models, it is clear that modelling networks to employ a single "Common Frequency" is the best strategy as opposed to "Multiple Frequency" network models.

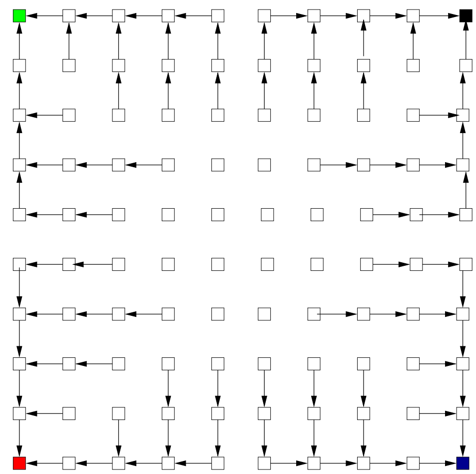
3.7 Conclusion

The *Gateway Selection* problem has been dealt in this chapter. We formulate an optimization model and subsequently propose polynomial time algorithms for each of the two network models described. We also provide interesting insights on some of the factors that must be considered while formulating gateway selection algorithms. We simulate these algorithms over a 10×10 grid network and indicate gateway positions for varying number of gateways (K). We also evaluate the performance of these algorithms for the case of 2 gateways over a 5×5 grid. As indicated in Sections 3.3.1, by permuting a gateway-pair over all nodes in the 5×5 grid and choosing the best gateway pair and its associated network throughput, we establish an upper-bound. The results of our gateway-selection algorithms are then compared to this upper-bound and shown to be within 15% of the upper-bound

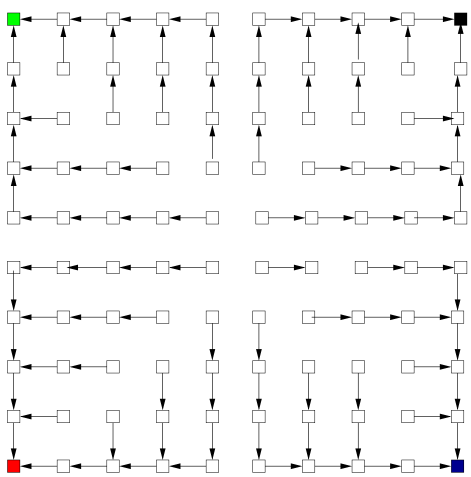
Finally, we compare the two networks proposed in Section 3 in terms of network performance. The practical issues associated with each of these networks are explained. Clearly, at the end of the study, it is evident that using the "Common Frequency" network model is the best strategy in modelling multi-gateway WMNs although the complexity of operating such a network model is far higher compared to its counter-part.



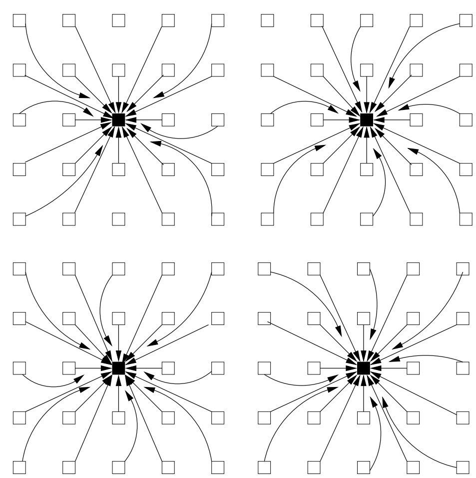
(a) Initial Phase



(b) Progress 1



(c) Progress 2



(d) Termination

Figure 3.23: Algorithm Growth for a 10 × 10 grid: a. Sector-heads with maximal SINR weights have been identified (3). The sector heads starts associating nodes. Here we indicate node association to the sector heads for the case of 2 hops and $K = 4$ gateways. b.The hop count for associating nodes has increased from 3.23. Here we illustrate node association for hop-count of 6. c. All nodes have been associated to respective sector-heads as is evident. d. The algorithm terminates by nominating cluster-heads in each of the cluster. Sector-heads have also lost their status and have associated themselves with the cluster-head (filled squares). Refer 3.2 for Gateway/Cluster-head nomination

Chapter 4

Conclusions and Future Work

4.1 Conclusions

At the start of this work, we set out to understand performance limits imposed by the use of different technologies in WMN. To that extent, we identified two broad technologies that are frequently used to improve performance in WMNs:

1. Smart Antennas in WMNs.
2. Multiple Gateways in WMNs.

4.1.1 Smart Antennas in WMN

Our efforts to understand the maximum capacity of smart antenna enabled WMNs has yielded interesting results. We now know that the maximum throughput achieved by single gateway WMN with/without smart-antenna is limited to $\frac{A}{N}$ (normalized to the highest data-rate A in a N-node mesh network). This is interesting since it clearly indicates the infeasibility of building large WMNs (single gateway serving a large number of nodes) with/without smart antennas. This is contrary to existing belief where several researchers have argued that the inherent spatial-reuse advantage associated with low-interference smart-antennas will yield high performance and offset the infra-structure costs associated with smart-antennas. Further, we are witnessing several interesting antenna technologies being developed to serve an array of applications. Each of these smart-antenna technologies bring in their unique set of pros and cons. Identifying the right technology and using this technology to build smart-antennas enabled WMNs will require detailed understanding of the technology and more accurate models, something that has been lacking in our study.

We do not intend however, that the use of smart antenna is not advantageous to the WMNs. Contrary to such claims, our study and Figure 2.3 reaffirms the advantages associated with smart antennas. We realize that the greatest advantage of using smart antenna lies in the low power range where there is a very significant increase in throughput compared to their omni-directional antenna counterpart. The use of smart antennas in designing high throughput WMNs hence, must be carefully studied in light of our study to identify the gains associated with these interesting technologies.

4.1.2 Multiple Gateways based WMNs.

The infeasibility of using smart-antennas to serve large WMNs clearly motivates us to explore other avenues. The use of multiple gateways in WMNs is a robust alternative to smart antenna enabled WMNs since performance scales with addition of more gateways in WMNs. Based on the operation, we have explored two types of multi-gateway WMNs and proposed algorithms to position gateways for each of these WMN models. Clearly, from the results, it is evident that in terms of network throughput performance, the gains associated with *Common Frequency* model outweigh the gains associated with the *Multiple Frequency* model. Such a result clearly indicates the impact of bandwidth on network throughput in-spite of the fact that using the *Multiple Frequency* model yields low-noise "cleaner" networks. As part of our study, we have established several bench-marks that is useful in designing algorithms.

4.2 Future Work

There are a number of avenues for future work. For the case of smart antennas in WMN, it is important that smart antennas are modelled more realistically incorporating side-lobes and/or back-lobes etc in the antenna model. Such precise models lend more insight into the WMN behaviour (throughput, routing, spatial reuse etc).

Moreover, in [9], it has been shown that computing the max-min throughput of arbitrary network is an NP-hard problem. However, by computing the bound on the maximum size of the "independent set" in the network, it has been shown in [9], that it is possible to compute the network throughput exactly under certain assumptions. The work of [9] however, models omni-directional antennas only. Owing to the inter-dependence of several parameters such as antenna beam-width and gain, side-lobe and/or back-lobe gain and beam-width on the network throughput and spatial-reuse, establishing such a bound for the case of smart antenna is a very hard problem. Hence, further research work is required in this direction as well. As smart-antenna technology matures and becomes more affordable in the future, it is only evident that more application scenarios will demand smart-antenna integration. It is hence important that precise antenna models and computational tools exist to fully exploit the advantages associated with these modern antenna technologies.

We have formulated a solution for the *Gateway Selection* problem by proposing algorithms that designate certain nodes as optimal gateways based on the SINR metric as explained in Section 3.2.2. It is interesting to study placement algorithms under more sophisticated link metrics. Several link metrics, for example, metrics that model traffic behaviour, hop-count, radius of transmission, etc are already being used to designate nodes as "optimal" gateways by various researchers. However, these metrics cater to WMNs incorporating single-power and single modulation-coding schemes. Link metrics that work on a range of input transmitter power levels yet yield optimal or close to optimal results are important and needs to be studied. Further, in Section 3.5, we have described the problem associated with locating gateways with close proximity to each other. Incorporating the idea of "independent sets" in algorithms will lead future algorithms to be more robust and circumvent this problem. Further, as explained in Section 3.6.2, proposing algorithms to work over a wide range of transmitter powers and/or modulation and coding schemes is a difficult problem. Algorithms which yield optimal results over a wide range of transmitter powers (and/or modulation-coding schemes) if not the complete range must be explored as well. Solutions for accurately solving the *Gateway Selection* Problem must be explored as well in order to avoid the approximations or sub-optimal results associated with algorithms.

Formulating and solving this problem in terms of a linear optimization model gives accurate results on gateway positions for any arbitrary node locations. Solving the problem accurately is important when compared to solutions using algorithms and hence must be explored.

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