ABSTRACT

PATHAK, PARTH H. Designing for Network and Service Continuity in Wireless Mesh Networks.
(Under the direction of Dr. Rudra Dutta.)

The paradigm of wireless mesh networks has matured in the last decade after extensive research and development. As opposed to the time of their inception, current mesh networks are expected to deliver carrier-grade access services to their users. With the increasing expectations, it is generally recognized that there is a lack of understanding of the level of service continuity that mesh networks can provide to its users. In this research, we address a set of network design problems and propose solutions to improve the service continuity of wireless mesh networks.

First, we investigate power control as a network layer problem in mesh networks. It is commonly acknowledged that reducing transmit power levels of nodes to the minimum required to retain connectivity always increases network capacity. In this work, we show that increasing power level of nodes can be beneficial in many cases depending on network's traffic and topological characteristics. With extensive analysis and simulations, we characterize achievable spatial reuse and capacity with respect to power control in various practical scenarios.

Second, we address the problem of generation of traffic hot-spots in wireless networks, and propose a novel power control scheme for load balancing. Using a heuristic based on the concept of centrality, we show that if we increase the power levels of only the nodes which are expected to relay more packets, significant relay load balancing can be achieved even using shortest path routing. Different from divergent routing schemes, such load balancing strategy is applicable to any arbitrary topology and traffic pattern.

With this understanding of power control and load balancing, we investigate the service continuity issues of an urban-scale mesh networks. We define and study two essential service continuity metrics - connection robustness (K-center availability) and performance robustness (K-center performability). K-center availability is the fraction of the time a mesh network is available to its users, while performability is a composite measure of performance (here - throughput) and robustness that captures aggregate experience of mesh users over a long period of time. We develop efficient algorithms for estimating these quantities for large urban-scale meshes and study their characteristics in various existing mesh networks. Our study reveals numerous novel insights that can help in designing mesh networks with high availability and performability.

While evaluating the performability, we used ideal case throughput performance estimation that ensures fair network resource allocation among the flows. Although this allows faster computation which is especially necessary for large state space exploration, it is difficult to implement in real-world using CSMA/CA MAC. To address this, we target the issue of unfair

and lower utilization of network resources in wireless networks. Specifically, in a mesh network, nodes closer to gateways often achieve a larger share of bandwidth resources while nodes farther away often starve for useful bandwidth. Using back-pressure utility maximization framework, we provide a solution to the issue of spatial bias that can be implemented using current 802.11 standards. To further increase the efficiency of back-pressure policy in mesh networks, we propose a dynamic packet aggregation scheme that is especially effective in Internet-like packet size distribution. Along the same lines, we use the back-pressure invariants to develop a variable channel width assignment scheme that can yield maximum benefits of using varying-sized channels while remaining fair in network-wide resource allocation.

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Designing for Network and Service Continuity in Wireless Mesh Networks

by
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DEDICATION

In memory of my late grandparents - **M. M. Brahmbhatt and M. G. Brahmbhatt**,

to my parents - **Devayani Pathak and Haresh Pathak**,

to my parents-in-law - **Nayana Vakharia and Devendra Vakharia**,

to my brother and sister-in-law - **Bhumin Pathak and Naimi Pathak**,

to my fiancée - **Jainy Vakharia**, and

to my sweetest little niece - **Aarya Pathak**.

BIOGRAPHY

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Chapter 1

Introduction

The paradigm of Wireless Mesh Network (WMN) was one of several which arose from the earlier concept of ad-hoc wireless networks. The mesh paradigm was seen as one characterized by static nodes with available electrical power, thus enabling high transmission power levels and increased geographic span. The mesh network further provides access to possibly mobile low-power clients which do not participate in routing or other network functions. The paradigm soon emerged as a potentially suitable solution for metropolitan area networks, providing last-few-miles (or last-few-hops) connectivity.

There are various attractive qualities of mesh networking, which include low-cost deployment, robustness and applicability to brownfield scenarios where installation of new ground fiber is infeasible, but Internet access is required. The mesh paradigm inherits useful characteristics from both the ad-hoc networking paradigm and the traditional wired infrastructure paradigm. In a way, the mesh paradigm might be seen to provide a middle ground between extreme regimes of wireless use. On the one hand, we can conceive of networks in which wireless links provide only last-hop links, connecting to a wired backbone - both WiFi and 2G/3G/4G networks may be seen as such cases, though the difference in technology makes for a very different span in the two cases. At the other extreme, an approach of exclusively wireless links to form a network with an arbitrary topology out of a significant number of nodes and an extended span has become mainstream for multi-hop wireless paradigms such as sensor, mobile ad-hoc, or tactical networks - such networks may not even connect to the wired backbone, or connect through a gateway as an isolated and separately managed network.

In this thesis, we address a set of design problems of wireless mesh networks with the central focus being service continuity. At a high level, we intend to enhance the understanding about the aspects of mesh network design those are not explored before in the light of their current applications. Current deployments of mesh networks are expected to support high availability services (as opposed to best-effort services) for them to compete with other access networks

such as cellular networks. In order to understand such requirements of mesh design, we analyze several aspects of their service continuity (availability, performability etc.) and provide insights about network planning and deployment. We published a comprehensive survey about network design problem and joint design approaches for mesh networks in [122]. Here, we start out the study with throughput capacity analysis at high transmission power levels, and then propose a load balancing scheme using transmission power control. We then study availability and performability of mesh networks which can help designers to establish useful SLA (Service Level Agreement) with users and providers. We then extend the study to develop design methods that can guarantee maximum utilization of network resources. Each of these contributions are listed in further details next.

1.1 Throughput Anomalies at High Transmission Power Levels

Transmission power of nodes in a mesh network affects the behavior of various protocols across the stack. This is because two fundamental characteristics of connectivity and interference are direct results of transmission power of nodes. It is generally acknowledged that reducing transmission power of nodes to the minimum such the network connectivity is retained always increases network throughput capacity. Any further increase in power increases interference and in turn reduces the spatial reuse.

In this work, we show that the effect of power control on throughput is much more complex than understood previously. Transmission power control can reduce the spatial reuse but can also reduce the number of hops in routing paths. This *range-hop* trade-off requires understanding a complex interaction between number of transmissions, spatial reuse and routing path lengths. We explore the trade-off using two contradicting power controls strategies proposed by *short-range-more-hops* Compow [111] and *long-range-fewer-hops* DirectTrans [87]. In Compow, all nodes use a uniform constant power level which is minimum required to maintain network connectivity. Compow achieves better concurrency in link scheduling but requires more relaying at nodes with longer routing paths. In sharp contrast to this, in DirectTrans, nodes willing to transmit increase their power level until receiver can be reached in single hop. DirectTrans benefits from fewer transmissions and no relaying but suffers with lower spatial reuse due to long high interference links.

We show that even though Compow and DirectTrans are two extremes of power control, their performance can be comparable in many cases. We study the range-hop trade-off in terms of achievable capacity with different traffic and topology patterns. It is shown that complex interplay of spatial reuse and total number of required transmissions determine the actual throughput at various levels of connectivity between nodes. Surprisingly, in many representative traffic patterns and network topologies, increase of power levels results in increased throughput.

As we shown in Chapter 3, in random topologies under uniform node-to-node traffic, minimally connected Compow and fully connected DirectTrans achieve almost equal throughput capacity. When network topology is even slightly clustered, increasing power levels of nodes results in better throughput (DirectTrans outperforms Compow). We show that *transitivity* of the Compow graph of any point pattern can be used to predict the behavior of throughput capacity with increase of power levels. In the highly realistic and practically important node-to-gateway traffic pattern, we show that increasing power level of the nodes always results in better throughput. We prove that WMNs achieve per node throughput of $O(1/\delta n)$, where δ is a factor dependent on hop-radius of the network, which in turn is dependent on power level of nodes. We have published all our analysis about power control and relevant results in [121, 118, 115] which provide first insights about anomalous behavior of throughput capacity at high transmission power levels.

1.2 Hot-spot Mitigation using Centrality-based Load Balancing

Based on the comprehensive analysis of power control, we next target the issue of unfair disproportionate relay load distribution using a novel power control scheme. Many routing protocols developed for wireless networks depend on shortest path routing (SPR) due to its characteristics of robustness, simplicity and scalability. The issue is that when hop count based shortest path routing is utilized for uniform node-to-node traffic, certain nodes have to relay disproportionate number of packets for others. These traffic hot-spots are created near the center in topologies where nodes are uniformly distributed, and near the periphery of clusters in clustered topologies. This increased congestion reduces the spatial reuse which in turn causes reduction in network throughput capacity.

The problem of traffic hot-spots has been addressed using divergent routing schemes in which routing paths intentionally avoid passing through the center. Examples of such routing strategies are Curve-ball routing [125, 95], Manhattan routing [137] and Outer space routing [106]. Such divergent routing schemes increase the relay load burden of nodes around the periphery to better utilize the resource while reducing the traffic load in the center. The advantage of improved load balancing comes at a cost of sacrificing the shortest path routing. This limits their applicability to certain topologies and traffic patterns only. Our central motivation is to provide a solution for load balancing where SPR and all its advantages are preserved.

As discussed in Chapter 4, we propose power control as a way of load balancing in wireless networks. It is shown that when transmission power of certain nodes are chosen intelligently, better load balancing can be achieved using SPR only. Here, data is routed on the shortest path only but the nodes that are expected to relay more packets are skipped (or jumped over) while choosing the next hop. Our power control-based load balancing scheme assigns higher

transmission power to nodes that are expected to relay more packets, and thereby reducing their relay load proactively. We use *betweenness centrality* to model the expected relay load and utilize it for power assignment.

Centrality-based power control changes the relay load profile of the network using improved load balancing. The scheme is applicable to any traffic pattern and topology as we show in [120, 117]. Also, improved load balancing helps a battery-operated network such as a sensor network in achieving improved energy efficiency and longer network lifetime. The discussion about energy efficiency in sensor networks was published in [116].

1.3 Service Continuity Analysis of Urban-scale Mesh Networks

The investigation of impact of power control on throughput capacity and load balancing gave us novel insights about deployment factors of an urban-scale large mesh network. Using this insights, we start out to study one of the salient characteristics of a mesh access network which is its robustness against component failures. A mesh topology provides resilience to link or node failures by enabling redundant routing paths between clients and gateways. In this work, we provide an in-depth study of this robustness characteristics of wireless mesh networks.

Current wireless mesh networks are expected to deliver carrier-grade services to its users. With these increasing expectations, it is generally being recognized that there is a lack of good understanding of level of service continuity that mesh networks can provide to its users. To address this, we study two essential service continuity metrics – connection robustness (availability) and performance robustness (performability). Availability of a network is the fraction of time a mesh network is available to its users. Performability is a joint metric of performance (throughput, delay etc.) and robustness that can capture aggregate experience of mesh users over a long period of time.

We define both service continuity metrics in Chapter 5, and develop efficient algorithms for estimating their values. The methods can be used to calculate availability and performability of large urban-scale mesh networks with as many as 500 nodes. We apply these methods to existing mesh networks and identify some crucial properties of deployment factors that directly impact the availability and performability measures. This is followed by a comprehensive simulation study (hundreds of hours of simulations) of deployment factors and service continuity metrics. The study reveals some of the fundamental design insights that are essential to design a highly available and performable mesh access network.

1.4 Improving Network Resource Utilization and Fairness

After addressing the issues of throughput capacity, load balancing, power control and service continuity, we move our attention to network resource utilization and fairness issues. The motivation behind the study came from the fact that performability evaluation in service continuity analysis required modeling throughput performance of a mesh network. Since performability study requires exploring a large state space, we used an estimation where network utilization is assumed to be fair among the flows. Although this allowed faster computation, it is difficult to implement in real-world using CSMA/CA MAC. To address this, we target the issue of unfair and lower utilization of network resources in a mesh. Specifically, it is known that in a wireless mesh network, nodes that are closer to gateway can get a larger share of gateway's airtime while nodes farther away from the gateway can starve for any useful bandwidth. This spatial bias and unfairness in network utilization requires additional gateway nodes which incurs higher deployment cost.

In this work, we use back-pressure framework of network utility maximization to enforce fair usage of gateway airtime. The back-pressure framework originally proposed by Tassiulas et al. in [149] has the potential of solving many fairness and network utilization related issues of wireless networks. In Chapter 6, we describe how the back-pressure scheduling and rate control can be implemented using CSMA/CA MAC with differential MAC layer priorities. The back-pressure policy ensures that each flow is served at its intermediate nodes with a service rate that is proportional to its differential backlog. We show that the mechanism can be used to mitigate the spatial bias of wireless mesh networks.

We show next that although the MAC priority-based implementation of back-pressure scheme on CSMA/CA works in experiments, it performs poorly when realistic Internet-type traffic is considered. Since there is a large variation in packet size of Internet traffic, the efficiency of serving the most backlogged queue in a neighborhood decreases. We address the issue by developing a packet aggregation scheme which adheres to the back-pressure invariants while performing the aggregation. As we showed in [54], this allows increased medium access and better service rate of backlogged queues which in turn results in unbiased network resource utilization.

Lastly, we design a cross-layer channel width assignment protocol that dynamically assigns higher channel width to starving back-logged queues. Since higher channel width ensures higher data rate and lower interference, the assignment aggressively serves the flows which can not achieve a fair share of network resources. Here, back-pressure policy is used to direct channel width assignment as we have described in [119] while maximizing the overall network utilization and ensuring bounded buffer occupancy.

Chapter 2

Background and Related Work

Wireless mesh network consists of wireless mesh routers and wired/wireless clients. Wireless mesh routers communicate in multi-hop fashion forming a relatively stable network. Clients connect to these routers using a wireless or a wired link. In the most common form of WMNs, every router performs relaying of data for other mesh routers (a typical ad-hoc networking paradigm), and certain mesh routers also have the additional capability of being Internet gateways. Such gateway routers often have a wired link which carries the traffic between the mesh routers and the Internet. This general form of WMNs can be visualized as an integration of two planes where the access plane provides connectivity to the clients while the forwarding plane relays traffic between the mesh routers. This design has become more and more popular due to the increasing usage of multiple radios in mesh routers and virtual wireless interfacing techniques.

Though WMNs inherit almost all characteristics of the more general ad-hoc network paradigm, such as decentralized design, distributed communications etc., there are a few differences. Unlike energy-constrained ad-hoc networks, mesh routers have no limitations regarding energy consumption. Also, the pattern of traffic between these routers is assumed to be fairly stable over time, more akin to typical access or campus networks, unlike sensor or tactical wireless networks. For this reason, WMN nodes can also have stable forwarding and routing roles, like more traditional infrastructure networks. In contrast, when WMNs are deployed for the purpose of short-term mission specific communication, they often act more as a tradition Mobile Ad-hoc Network (MANET). Here, the majority of the traffic flows between mesh routers (not always to the gateways as in previous case) and even clients may communicate with each other directly. This kind of architecture is referred to as a hybrid mesh [31] and is one of the promising and emerging vision for the future of WMNs.

There can be pre-planned (usually centrally controlled) as well as comparatively unstructured and incremental deployment of nodes in WMNs. In the recent past, there have been many

attempts to design community wireless networks using unstructured deployment of WMNs. In such Wireless Community Networks (WCNs) [56], users own the mesh routers and participate in the network to facilitate access to other users for mutual benefit. In developed areas, the fundamental objective of such an unplanned deployment/expansion is to develop an Internet connectivity blanket for anywhere, anytime connectivity [35]. Also, WMNs deployment has been proposed as reliable and affordable access networks in underdeveloped regions. Here, the aim is to design a network as a low-cost access initiative (often by Internet Service Providers) to aid the development of communities. WMNs benefit from incremental expansion because their robustness and coverage increases as more and more mesh routers are added. These benefits of WMNs consistently motivate researchers to study their characteristics for better performance.

Two other fundamental benefits of WMNs are their ease of deployment and affordable cost. To achieve them, majority of current deployments are based on the IEEE 802.11 standard. This by no means restricts the WMNs' applicability to other standards but cheap availability of 802.11 hardware has mostly motivated this growth. Because the 802.11 software stack was originally designed for infrastructure WLANs, various modifications are necessary when using it in WMNs. Researchers are actively investigating these modifications, and the majority of efforts are directed towards design of better link layer and channel access protocols. Meanwhile, other standards like WiMAX [27] and 3G/4G are emerging and knowledge gained by research and development of WMNs over 802.11 is likely to be very useful in the future in these diverse contexts. We first review some of the mesh testbeds and deployments to understand how they are necessary in studying cross-layer protocol design.

2.1 Experimental Mesh Testbeds, Real-world Deployments, Emergence of Joint Design

Simulation based studies of wireless ad-hoc networks have been long conducted and it is known that there is a significant gap between the actual measured performance and simulation results. In the last few years, increasingly cheaper and more accessible technology has allowed researchers to undertake actual testbed based evaluation of protocols. This has lead to research and development of a plethora of mesh testbeds. However, the development of such testbeds also made clear for the first time the critical importance of jointly considering traditionally isolated design problems, because the testbed designer has to make some decisions, if only by default, about the issues that are not of central interest to the research problem at hand. In simulation, it might be feasible to study the relative performance of two particular routing algorithms without making any reference to the medium access approach underneath, but an actual testbed has to use some actual MAC. Moreover, the answer to the comparative performance

question may well change depending on what MAC is used – or even details in its configuration, such as the carrier sense threshold of 802.11. Such testbeds thus spurred the quickened interest and explosive growth of the joint design research area that this survey is focused on, and in turn provide the proving ground for such research. The study of joint design in WMNs is thus also, in part, a study of research issues in WMN testbeds. Below we provide only a very brief overview to motivate our discussion on joint design; a full survey of mesh testbeds is outside the scope of this paper and merits a separate discussion.

Examples of such testbeds include MIT Roofnet [16], CuWiN [7], CentMesh [4], Mesh-Net [13], WiseNet [28], Mesh@Purdue [21], Broadband Wireless Networking (BWN) lab [3], SMesh [33] etc. Some testbeds like Orbit [19] and Emulab [8] provide flexible platform to other researchers who can test their methodology or protocols on them. Such efforts have given rise to many open source implementations of protocols, device drivers and network applications. Several research efforts are directed towards making community based mesh networks more and more self-organizing and cooperative [15] where every participant contributes to the network resources.

Mesh testbeds nodes are typically small single board embedded computers like Soekris boards [23] or medium capacity machines like VIA EPIA mini-ITX motherboards [26] or high capacity desktops. When using off-the-shelf hardware, wireless cards using Atheros 802.11 chipsets are often used due to their open source driver support like MadWifi [11] and recently Ath5k and Ath9k [2]. Though testbed experimentations result in precise evaluation, they are often time-consuming, costly and inflexible. To overcome such issues, scaled-down, smaller transmission range versions of actual testbeds such as ScaleMesh [58] and IvyNet [145] can also be used. Sometimes a combination of simulation, emulation and real-world testbed experiments are used [114] or testbeds are deployed with advanced operating system virtualization techniques [164], [163] to improve the testbed control and management.

There is a diverse range of application scenarios for wireless mesh network deployment; this is another issue which significantly affects the perceived performance of various isolated design approaches. The fundamental objective of mesh deployment has been low-cost Internet access. Mesh networks deployed in communities spanning small or medium sized areas can be a very good business model for ISPs to provide Internet access. TFA Rice mesh [47], Google Mesh [9], Ponca city mesh [20] are a few of the examples of such deployments. With recent awareness about using alternate sources of energy, many of the wireless mesh routers are also designed to run with solar energy and rechargeable batteries [24]. This will certainly give rise to mesh deployments in near future where mesh routers running on solar energy can be fixed on apartment roofs or light poles, forming a mesh in neighborhood areas. Mesh networks can also serve the purpose of temporary infrastructure in disaster and emergency situations. Various control systems such as public area surveillance can also be operated using WMNs. Other applications

considered for WMNs include remote medical care [147], traffic control system [93], public services [39], integration with sensor monitoring systems [153], [156]. Considering these plethora of applications, many vendors have started providing mesh based network solution for broadband Internet access. Cisco Systems [6], Meraki Networks [12], Tropos Networks [25], Ruckus Wireless [22] and Aruba Networks [1] are some examples of commercial WMN vendors.

2.2 WMN Design Challenges

Research challenges in WMN design can be traced to network characteristics and motivations in deployment. The reason that WMNs are often seen as the last few miles network is the possibility of easy retro-fit: the coverage area of standards like WLAN can be extended further without the requirement of any specific infrastructure. Due to their mesh nature, an ideal WMN also has the properties of robustness and self-management. These imply a more ad-hoc model than the more traditional infrastructure model of access or campus area networks. Such a model poses various challenges for designers. Increasing scalability with expansion, novel MAC design, interference mitigation techniques, heterogeneity amongst standards are a few of these challenges. We motivate below the fundamental problems, and design objectives, that affect the performance of WMNs and discuss them in details. Tables 2.1 and 2.2 summarize this overview, and cites a few of the representative contributions in the related field.

Every transmission between wireless mesh routers creates interference in its neighborhood, which is a major issue challenging the performance of WMNs. On one hand, certain high power level for transmission is necessary for successful reception at the receiver. On the other, high power transmission causes high interference and MAC layer collisions at other unintended receivers. Various attempts have been made to model the effects of interference using abstract theoretical models as well as measurement-based models. Adopting the knowledge of interference from such models, researchers have designed protocols for power control, link scheduling, routing and channel/radio assignment. Energy conservation not being an objective, power control and topology control mechanisms in WMNs mainly deal with assigning transmission power levels to nodes such that the traffic demands are satisfied with better overall throughput. The parallel objective of any such mechanism is also to reduce interference, which in turn increases the achievable network capacity.

Power control and topology control mechanisms determine the network connectivity and underlying physical layer topology. All links of such a topology can carry the traffic between the nodes, and the reception rate depends on the quality of the link. Routing strategy determines reliable and high throughput end-to-end paths between the source and destination of data. Various characteristics of links such as quality, stability and reliability play an important role in routing metric design which is used by the routing protocol. Link scheduling strategies estimate

Table 2.1: WMN design problems - Interference modeling, power control, topology control, link scheduling, channel/radio assignment

<p>Interference measurement and modeling - Tractable yet realistic estimation of interference in dynamic wireless environment.</p> <p>Objective: Design of abstract interference models to aid upper layer protocol design and their comparison to actual measurements, link and network capacity analysis.</p> <p>Sample Literature: Protocol and physical interference models [74], scalable measurement based estimation of interference and packet delivery [131]</p>
<p>Power control - Assigning transmission power levels to nodes having transmission requirements.</p> <p>Objective: Minimizing interference, avoiding MAC collisions for better network capacity and throughput, energy conservation (some special cases of WMNs).</p> <p>Sample Literature: Motivations and requirements of power control mechanism [84], uniform power assignment [111], variable range power control [97]</p>
<p>Topology control - Choosing or avoiding certain links in network.</p> <p>Objective: Interference mitigation and reducing MAC layer collisions.</p> <p>Sample Literature: MST-based low interference topology design [46]</p>
<p>Link Scheduling - Scheduling link transmissions to achieve feasible and conflict-free transmission schedule.</p> <p>Objective: Higher throughput and better spatial reuse, efficient medium access and utilization, fairness.</p> <p>Sample Literature: Stability property for scheduling in multi-hop networks [149], link scheduling in protocol interference model [80] and physical interference model [45]</p>
<p>Channel/radio assignment - Assigning multiple channels to single or multiple radios at nodes.</p> <p>Objective: Separation in frequency domain to increase concurrent transmissions and thus throughput.</p> <p>Sample Literature: Motivations and challenges in multi-channel multi-radio mesh [91], channel assignment using interference conflict graph based vertex or edge coloring [146], multi-radio conflict graph based centralized channel assignment [129]</p>

transmission conflicts between links of these routing paths using the interference model and try to achieve a conflict-free feasible transmission schedule. There are various challenges in distributed implementation of any such scheduling scheme which combines medium access, collision detection/avoidance and transmission scheduling techniques. Spatial reuse (concurrent transmissions on more than one links) can be increased when non-interfering links are scheduled in parallel using intelligent scheduling. To further mitigate the interference effects, interfering links are often separated in the frequency domain. Channel/radio assignment schemes try to arrange nearby transmissions on orthogonal or minimally overlapping channels in single or multi-radio WMNs.

Table 2.2: WMN design problems - Routing, rate control and congestion control, network planning, performance modeling

<p>Routing - Choosing routing paths to satisfy end-to-end traffic demands between nodes.</p> <p>Objective: Low inter-path and intra-path interference, load balancing and hot-spot mitigation, higher reliability and throughput.</p> <p>Sample Literature: Channel quality and diversity in multi-channel single-radio [144] and multi-channel routing [55], opportunistic routing protocol [41], hot-spot analysis with straight line routing [90]</p>
<p>Rate control and Congestion control - TCP-like congestion control methods that work despite loss and bias introduced by wireless medium, including multihop.</p> <p>Objective: Throughput, congestion control, fairness.</p> <p>Sample Literature: general TCP survey [100], addressing spatial bias [103],</p>
<p>Network planning and deployment - Topological and deployment factors, gateway placement.</p> <p>Objective: Network expansion in non-cooperative environment, load balancing with intelligent gateway placement.</p> <p>Sample Literature: Study of deployment and topological factors [133]</p>
<p>Performance modeling and capacity analysis - Understanding best and worst case theoretical capacity.</p> <p>Objective: Performance analysis and estimation of system capacity and newly developed protocols.</p> <p>Sample Literature: Best case theoretical throughput of WMNs [74], Capacity of multi-channel WMNs [92]</p>

It is well understood among researchers that the above mentioned problems are highly interrelated. For example, it may happen that link scheduling does not yield a high throughput schedule because of the existence of high interference links in the network. This may require the traffic of such links to be re-routed on shorter and lower interference links. This points the way to treating link scheduling and routing as a joint problem. Over the course of several years of research, it has become obvious that dealing with these interdependent problems jointly is preferable (indeed, almost unavoidable) in optimizing performance.

2.3 Transmission Power Control

The problem of power control deals with assigning power levels to the nodes having transmission requirements in such a way that a particular objective is achieved, while still maintaining network connectivity as a fundamental requirement. Such an optimization objective can be lower interference, higher throughput and sometimes power conservation. Power control mechanisms proposed in the literature can be largely classified as follows.

Static Power Control

A static power allocation assigns power levels to the nodes that do not change frequently over time, unless there are drastic changes in the network topology. Such mechanisms are simpler and more robust but often result in suboptimal performance due to their inefficient adaptation of changing traffic demands and dynamic wireless conditions. Static power control mechanisms presented in the literature can be further classified in uniform or variable range power control.

In seminal work on static power control, it was shown in [111] and [84] that throughput with all nodes operating at one common power level (Compow), that which is minimum required for maintaining network connectivity, is nearly optimal. It is shown that such common power level can achieve the best case capacity ($\Theta(1/\sqrt{n})$ bits/sec [74]) with optimal node deployment. It is also near optimal ($\Theta(1/\sqrt{n \log n})$ bits/sec) even in the case of random networks, without requiring any complex mechanism.

Uniform range power control protocols like Compow have their disadvantages, one of which is that the common power level can be very high in non-uniform clustered topologies. This issue gave rise to many variable range power control protocols. In variable range power control, different nodes in the network use different power levels. Such levels are often determined based on the node locations, overall network connectivity, tolerable interference and even routing paths. It is shown in [71] that variable-range transmission power control, where every node dynamically controls the transmission power, can outperform the Compow approach [111] in terms of traffic carrying capacity of the network. It proposes a Minimum Spanning Tree (MST) based variable-range power control to maintain the network connectivity and increase the capacity. Specifically, it is shown that routing protocols based on such variable power levels can achieve twice the traffic carrying capacity than routing protocols based on common-range power control. An important result in [71] indicates that with variable power control, the average traffic carrying capacity remains constant even if more nodes are added to the network; this result is in contrast to the results presented in [74]. Along the same line, [97] makes the first approach to overcome the disadvantages of uniform power assignment by building a decentralized Minimum Spanning Tree (MST) based topology; the algorithm presented uses transmission power or Euclidean distance (linear with power) as the weight of an edge in the network graph, and tries to build a minimum (power) spanning tree connecting all nodes. Every node determines its one hop on-tree nodes to be its actual neighbors, and the overall topology is built by integrating the MSTs of all nodes and maintaining symmetric links. Such a topology can maintain a lower node degree which is shown to reduce interference and MAC-level collisions.

Some of the previous power control and topology control mechanisms aimed to minimize the overall power consumption in traditional ad-hoc networks. With increasing outdoor deployments of wireless mesh networks, there is an opportunity to utilize alternate sources of energy, like

solar energy, to operate the wireless routers. Power consumption still remains an important objective of any power assignment mechanism. The study of [82] proposes several approximation algorithms for finding a power assignment of nodes in wireless ad-hoc network such that the topology graph is k -connected (i.e., it remains connected upon removal of fewer than k vertices) and the total power utilized is the lowest. Wireless links often display unpredictable behavior and hence such fault tolerant topology holds importance in terms of survivability in WMNs. As defined in [82], an i -nearest-neighbor subgraph of G is a spanning subgraph of G in which there is an edge between two nodes u and v if and only if either u is one of the i nearest neighbor of v in G , or vice versa. A subgraph F of G is called a k -connectivity augmentation to H if $H \cup F$ is a k -connected spanning subgraph of G . The algorithm of [82] first constructs the $(k-1)$ -nearest neighbor graph $G(k-1)$ from the maximum connected topology and then finds a k -connectivity augmentation F to $G(k-1)$ and outputs $G(k-1) \cup F$ with the desired property.

Dynamic Power Control

With dynamic power control strategies, every node changes its power level for transmission frequently over the time. Such changes can be made on per link, per destination, per TDMA slot or per packet basis.

Many proposed mechanisms perform the power allocation locally at every node based on the current condition of its neighbors. The PATE (Power Assignment for Throughput Enhancement) algorithm [158] is one such approach; it tries to avoid congested neighbors by choosing next-hop nodes which are less loaded. Power assignment is performed in such a way that connectivity of the network is maintained while the least congested neighbor which will create less interference to other nodes is chosen. A cost function is presented to determine the neighbors, and the corresponding required power levels to reach them. The study of [107] proposes the Power Control Multiple Access (PCMA) MAC protocol where the transmitter chooses the transmit power level based on how much interference the receiver can tolerate. It uses a separate control channel to send “busy tone signals” which advertise the tolerance levels. Similarly, Power Controlled Dual Channel (PCDC) [108] uses a separate control channel for advertising the interference tolerance. Though both PCMA and PCDC result in increased throughput due to informed decisions regarding power control, both assume wireless devices can transmit and receive at the same time on control and data channel; this requires an additional radio for each communicating device. This limitation was addressed in [109] which also proposed an improved power control protocol. POWMAC [109] uses an access window to allow for a series of RTS/CTS exchanges to take place before several data transmissions can take place concurrently. The received signal strength is then used to dynamically bind the transmission power of potentially interfering terminals in the vicinity of a receiving terminal. The required transmission power

of a data packet is computed at the intended receiver, to allow for some interference margin at the receiver. This will allow multiple transmissions to take place concurrently in the neighborhood. Though POWMAC achieves concurrent transmissions using one channel only, sometimes contention may occur during the access window.

The problem of power assignment becomes even more complex when decisions must be made in a distributed fashion, with limited information available locally. To simplify the design, [30] proposes a feedback based fall-back power control algorithm. If a pre-determined number of transmissions are successful, the sender decrements the transmission power level until it reaches the lowest required power level without affecting the intended data rate. While decreasing power, if it encounters data loss at a certain level; it starts incrementing power level until it recovers the data rate (or reaches the highest possible power level). With the objective of power allocation in a decentralized network, [141] formulates power allocation as a problem in which interference (caused by transmissions of other users) is viewed as an external emergent condition by nodes, quantified in an “interference temperature”. The approach presented tries to satisfy the interference temperature constraints and maximize a function of the sum of users’ utilities.

In the IEEE 802.11 MAC standard, whenever a node wishes to transmit, it first senses the medium; if the sampled signal strength is below the carrier sense threshold, it initiates the transmission. The value of the threshold and transmit power together dictate when and at what power level a node transmits. All combinations of these two quantities may not be useful; [63] argues that the product of transmit power and carrier sense threshold should be a constant for each transmitter in the network. Based on such a mechanism, nodes transmitting at large power levels should use lower carrier sense threshold because they cause more interference to others and should be more careful before initiating their transmission. As in [88], the spatial reuse can be increased in wireless multi-hop networks such as mesh by either reducing transmission power, or increasing the carrier sense threshold. The study of [88] shows that there is a trade-off between the level of spatial reuse and the data rate that can be sustained by a transmission. It also shows that if the achievable channel rate is a continuous function of SINR, network capacity depends only on the ratio of transmit power to the carrier sense threshold. When the set of channel data rates available are discrete (as in realistic protocols like 802.11), tuning the transmission power while keeping the carrier sense threshold constant can achieve more advantages. Finally, [88] provides a localized power and rate control algorithm, where the transmitter monitors the current interference, and determines the power level accordingly. The algorithm chooses a power level in such a way that sender can sustain maximum possible data rate and the interference caused by it to other nodes is minimum. Similarly, [160] concludes that higher throughput can be achieved if area silenced by the transmitter is reduced as much as possible while covering the interference area (containing the set of nodes that would cause collision at the receiver, if they also transmitted) of the receiver.

Different from all the approaches studied before in literature, our primary interest is to determine the effects of high transmission powers on throughput. We are interested in studying how increase of transmission power decreases routing hops while decreasing spatial reuse at the same time, and affecting the overall throughput capacity. We will study this *range-hop tradeoff* in Chapter 3.

2.4 Relay Load Balancing

The shortest path routing is most commonly utilized routing strategy due to its computational feasibility, robustness and performance characteristics. When shortest path or straight line routing is used, most of the routing paths pass through a certain region (center of network) creating a highly congested, security-prone area. Nodes in such area have to relay disproportionate amount of traffic for other nodes and often suffer from severe unfairness. Recently, [90] showed that relay load on the network mainly depends on the offered traffic pattern. When shortest path routing is used with random traffic pattern, it can give rise to different load distribution, generating hot-spot at different places in the network.

The Problem of modeling the relay load of nodes in network has been addressed by a few research efforts. For uniform topologies, relay load is often modeled as a function of node's distance from the center [125], [94]. Recently, the relay load of a node has also been modeled probabilistically as a function of the perimeter of the node's Voronoi cell [90]. Though such modeling works for uniform topologies and traffic, relay load estimation in arbitrary topologies is still an open problem. Similarly, finding ways to evenly distribute the relay load in the network is also an open research issue and is being actively investigated. Current approaches for relay load balancing depends mainly on transforming Euclidean network graph on symmetric spaces like a sphere or a torus which do not show such *crowded center* characteristics. Many *divergent*, *center-avoiding* routing mechanisms described below have been proposed by researchers to try and balance the relay load among the nodes.

- *Curve-ball Routing*: [125] and [95] present an approach for load balancing in which stereographic projection is used to map the Euclidean node positions on a sphere. The routes between the source and destination are then found using great circle distance on sphere and then they are mapped back to the actual plane in network. Such routes often results in circular arc shaped forwarding which is claimed to be distributing the load in network since they intentionally avoid passing through the center.
- *Outer-space Routing*: [105] proposed the concept of routing in outer space in which original network space is mapped onto a symmetric outer space (torus). The shortest routing paths between nodes in such outer space will symmetrically distribute the relay load in the entire

network. Such paths are then used for routing in the original network to avoid routing via hot-spots.

- *Manhattan routing*: [137] proposed a divergent routing scheme in which source forwards the packet to an intermediate node which is near the intersection of horizontal/vertical lines passing through the source and destination.

Similarly, several other similar load balancing mechanisms are described and analyzed in [10]. As shown in [96] and [65], such routing mechanisms display trade-off between stretch-factor of routing paths and actual load balancing.

As we will see in Chapter 4, divergent routing schemes have limited applicability and we will design a power control based load balancing scheme to address the issues.

2.5 Service Continuity in Wireless Mesh Networks

In Chapter 5, we study the availability and performability of urban-scale wireless mesh networks. We discuss the related literature in Chapter 5 with better context, and only briefly describe it here.

Different from various other approaches in literature which focus on deriving asymptotic results [40, 157, 77] for network connectivity, *we are interested in numerical evaluation of network availability*. Apart from connectivity and performance related research, exact evaluation of reliability of mesh networks was recently studied in [57] and [47]. The approach presented in [57] assumes a single gateway topology and is not scalable to large networks. The method of finding reliability presented in [47] considers multiple gateways but assumes fixed gateway-mesh nodes association. Also, it requires finding all possible paths from every mesh node to its gateway and assumes that failure of a path is independent of any other path. Due to these simplifying assumptions, it yields an inaccurate reliability estimate. To best of our knowledge, performability in mesh networks has not been studied previously.

We will discuss the back-pressure framework and related work regarding packet aggregation and channel width assignment in Chapter 6.

Chapter 3

Analyzing Impact of Power Control on Throughput Capacity

In this chapter, we consider power control as a network layer problem in wireless mesh networks. The network connectivity between nodes is determined by their communication range which in turn can be controlled by adjusting the transmit power level. It is generally acknowledged that reducing transmit power levels of nodes to the minimum required to retain connectivity always increases network capacity. In this work, increasing power level of nodes can be beneficial in many cases depending on traffic and topology characteristics. Based on analysis and simulations, it is observed that increasing power levels of nodes (and decreasing number of hops in routing paths) results in increase of throughput in many representative traffic patterns and topologies. We characterize achievable spatial reuse and capacity with respect to power control in different topologies and traffic patterns.

3.1 Problem Description - The Range-hop Trade-off

In a wireless mesh network, throughput behavior depends on *range-hop* tradeoff of various power control strategies. The trade-off is best characterized by two contradicting power control strategies proposed by *short-range-multi-hop* Compow [111] and *long-range-single-hop* DirectTrans [87]. In Compow, all nodes use a uniform constant power level which is minimum required to maintain network connectivity. Compow achieves better concurrency in link scheduling but requires more relaying at nodes with longer routing paths. In sharp contrast to this, in DirectTrans, nodes willing to transmit increase their power level until receiver can be reached in single hop. DirectTrans benefits from fewer transmissions and no relaying but suffers with lower spatial reuse due to long high interference links.

Fig. 3.1 shows an example which demonstrates the trade-off. Assume that there are three

Figure 3.1: (a) Compow graph (b) DirectTrans graph

flows $v_1 \rightarrow v_3, v_3 \rightarrow v_5, v_5 \rightarrow v_1$, each transferring one unit of traffic. Also, assume that shortest path routing is used and 2-hop interference model determines sets of mutually interfering links. In Compow topology (left), all the six links have to be scheduled once to satisfy traffic demands of three flows. Links of the same color represent a set of links which have to be scheduled once and do not mutually interfere. Routing path for every flow in this case contains two hops. When TDM scheduler is used to schedule the links, three slots are required to complete the transmission demands since two links can be scheduled in each of the three slot (e.g. v_1v_2 and v_4v_5). On the other hand, in DirectTrans topology (right), all nodes are directly in one hop reach of all other nodes (clique). In this case, only one transmission is required for every flow but each of the transmission interferes with all other transmissions (e.g. v_1v_3). The spatial reuse in this case drops to one, also requiring three slots for satisfying traffic demands. This way, even though Compow and DirectTrans are two extremes of uniform power control, their performance can become comparable in WMNs.

In this chapter, we study the shorter-hops-longer-paths and longer-hops-shorter-paths trade-off in terms of attainable capacity with different traffic patterns and topologies. It is shown that complex interplay of spatial reuse and total number of required transmissions determine the actual throughput at various levels of connectivity between nodes. Surprisingly, in many representative traffic patterns and network topologies, increase of power levels results in increased throughput. We will primarily consider TDMA as link scheduling and medium access strategy due to its analytical tractability. We then verify the results with CSMA/CA MAC using simulations.

Some of the important results of the chapter are as follows:

1. In random topologies under uniform node-to-node traffic, minimally connected Compow and fully connected DirectTrans achieve almost equal throughput capacity. (Sec. 3.4.1)

2. When network topology is even slightly clustered, increasing power levels of nodes results in better throughput (DirectTrans outperforms Compow). We show that *transitivity* of the Compow graph of any point pattern can be used to estimate the behavior of throughput capacity with increase of power levels. (Sec. 3.4.3)
3. In the highly realistic and practically important node-to-gateway traffic pattern, we show that increasing power level of the nodes always results in better throughput. We prove that WMNs achieve per node throughput of $O(1/\delta n)$, where δ is a factor dependent on hop-radius of the network, which in turn is dependent on power level of nodes (Sec. 3.5).

These results provide first insights about behavior of capacity with power control in different topologies and traffic patterns when nodes use high transmission power levels.

3.2 Network Model and Methodology

We model the network graph using unit disk graph $G_U = (V, E, \lambda)$ where V is the set of nodes and for any two nodes u and v , there exists an edge $uv \in E$ if their Euclidean distance $d_{uv} \leq \lambda$. Compow range (d_{min}) is defined as minimum value of λ such that G_U is connected. Similarly, DirectTrans range (d_{max}) is minimum value of λ such that G_U is *fully* connected (clique). We refer to the Compow graph of V as $G_C = (V, E_C, d_{min})$ and DirectTrans graph as $G_D = (V, E_D, d_{max})$. We have proved that d_{min} is the value of maximum edge weight in Euclidean minimum spanning tree of V (also asserted, but without proof, in [138, 123]). The proof is presented in Appendix A; we mention it only in order to state that this result allows us to efficiently determine d_{min} for large set of nodes using any known polynomial time algorithm.

As we stated, our principal problem is to investigate the impact of changing power levels of nodes on throughput capacity in different topologies and traffic patterns. We approach the problem by using *uniform power control* method of increasing power levels and communication range. In uniform power control, all nodes increase their power levels step-by-step by a common factor such that at any step, they all operate at the same power level. Here, increase in power levels can actually be interpreted as bounding the maximum power level of nodes. That is, if a node increases its power level, this does not mean that it will always transmit at new increased power level. If a neighbor is reachable at a lower power level, it will utilize that to communicate with it.

We use path loss model of signal propagation. If transmitted signal power is P_t and distance between the transmitter and the receiver is d then received signal power (P_r) attenuates as $P_r \propto P_t(d^{-\alpha})$, where α is the path loss exponent which depends on environment ($2 \leq \alpha \leq 5$). Let β be the receiver sensitivity threshold such that signal is properly decoded at the receiver if $P_r \geq \beta$. The communication range of a node is the distance at which $P_r = \beta$ in absence of any

other interference. Now, power level of nodes can be presented in terms of their communication range. As an example, in G_C all nodes are operating at power level $P(d_{min})$ which is necessary and sufficient to achieve communication range of d_{min} at all nodes.

During the uniform increase of power levels, every node increases its communication range by a factor of f from the Compow range. This is achieved by tuning its power level to $P(f \cdot d_{min})$. This way, increase of power levels are normalized to the Compow range (d_{min}), not to the Compow power level ($P(d_{min})$). We refer to f as the *growth factor* of connectivity. In all cases, two widely used traffic patterns namely, *uniform node-to-node* (Sec. 3.4) and *uniform node-to-gateway* (Sec. 3.5) are studied. In uniform node-to-node traffic pattern, every pair of source and destination communicate with amount of traffic which is uniform across all such pairs. In uniform node-to-gateway traffic, all nodes send uniform amount of traffic to the gateway only. Also, since the study pertains to wireless mesh networks (not energy-constrained), nodes do not have any restrictions on available power resources. Without loss of generality, we assume that all nodes operate on the same channel. Problems like channel assignment, physical layer rate adaptation etc. are orthogonal to the work presented here.

Even though the central focus of this study is based on TDMA medium access protocol, we show that some of the general characteristics of range-hop tradeoff also extends to CSMA MAC protocol. This claims are supported with numerical results whenever applicable.

3.3 Throughput Capacity

TDMA-based link scheduling problem as described above is known to be NP-hard for following interference models -

1. Protocol interference model [55],
2. K-hop interference model (where $K \geq 2$) [140],
3. SINR-based additive physical interference model [72]

The focus of this work is not to develop an efficient scheduling algorithm but to understand the effects of power control on capacity when the links are TDM-scheduled. Hence, we use greedy link scheduler for generating time slotted, conflict-free and feasible link transmission schedule and compare its performance with bounds derived on optimal schedule. Similar greedy scheduling algorithms have been proposed in [45] and [118] for physical and protocol interference model respectively. As we will see, the performance of the greedy scheduler is within a constant factor from the optimal schedule.

3.3.1 TDMA Greedy Link Scheduler

First, we briefly describe the TDMA greedy link scheduler [118] and then proceed with the discussion of throughput capacity in various cases. The end-to-end traffic demand between nodes is represented using a traffic demand matrix (T_R). Once the shortest path routing is performed, T_R yields per-link transmission matrix (T_X). We assume that there is a central controller entity which performs link scheduling. In operation of the greedy scheduler, first all links of T_X are sorted based on their interference score. Interference score of a link is the number of other links with whom the given link interferes and hence can not be scheduled simultaneously. Then scheduler chooses the first link in order to be scheduled in the current slot and tries to add more and more non-interfering links greedily until no more links can be added to the slot. The procedure repeats until all transmission requests of T_X are satisfied. [45] showed that such a scheduler has the time complexity of $O(m \cdot n \cdot T)$, where $T = \sum_{i=0}^n \sum_{j=0}^n T_{X_{ij}}$. If the total offered load $G = \sum_{i=0}^n \sum_{j=0}^n T_{R_{ij}}$ and greedy scheduler requires S slots to schedule all the links, the network throughput is G/S traffic units per unit time.

We assume that simultaneous transmissions on two links uv and xy results in collision-free data reception at the receivers iff $d_{ux}, d_{uy}, d_{vx}, d_{vy} > (\Delta \cdot d_{uv})$ and $d_{ux}, d_{uy}, d_{vx}, d_{vy} > (\Delta \cdot d_{xy})$, where d_{xy} is the distance between nodes x and y and interference ratio $\Delta = 2$. Such a consideration of interference in greedy scheduler allows us to focus on network connectivity without delving in physical layer details such as physical layer data rate, signal quality etc. Using this knowledge, now we move on to the capacity analysis and results for different traffic patterns and topologies. First, we consider a more general case of uniform node-to-node traffic and then look at WMN specific uniform node-to-gateway traffic pattern.

3.4 Uniform Node-to-node (N2N) Traffic

In all cases, growth factor f is used to uniformly increase the connectivity such that the resulting network graph transforms a minimally connected Compow graph (G_C) to a completely connected DirectTrans graph (G_D). It is worth acknowledging that the power level required to achieve DirectTrans range at each node might be very high and practically impossible. We still include this extreme case in study because step-by-step transformation of network graph from Compow to DirectTrans facilitates various intermediate levels of connectivity which are practically feasible and provide better understanding of general behavior of throughput capacity.

3.4.1 Uniform Topology

When the nodes are distributed with uniform density in the plane, transmission *footprint* based analysis can be used to calculate the average spatial reuse. Though this is a simplification of

actual disk packing based analysis, we will see that the proposed method yields close approximation of theoretical capacity.

Let l denote the length of the side in a square network area and let G be the total offered load (N2N), that is $G = \sum_{i=0}^n \sum_{j=0}^n T_{R_{ij}}$. Let $\lambda = d_{min}$ denote the Compow range for the given node placement. At every state of uniform power increase, communication range ($f\lambda$) and interference range ($\Delta f\lambda$) of nodes also increase. Based on the interference model, every link transmission occupies a wireless footprint in shape of a overlapping double disk. Such a double disk is created by having one disk of radius $\Delta f\lambda$ at each end points of the link. Now, the best case of spatial reuse can be considered as tightly packed double disks of links in the network area, each with radius of $f\lambda$ only. This is when end points of two active links have overlapping interference ranges but their communication ranges do not overlap. With the radius of $f\lambda$, expected value of area of such overlapping double disk of every link is approximately $5(f\lambda)^2$. No other transmission can be concurrently scheduled in this area without causing interference to ongoing transmission. Thus, average spatial reuse in any slot can be approximated by (network area / expected value of area of double disk) = $\frac{(l+2f\lambda)^2}{5(f\lambda)^2}$. Considering $(l + 2f\lambda)$ for the calculation of network area allows better consideration of link transmissions over the boundary of the network at least when $l \gg f\lambda$.

Let L denote the average distance between any source-destination pair in the network. With the employment of shortest path routing and assumption of uniform node density, average path length in terms of hops can be approximated as $\frac{L}{f\lambda}$. Total number of link transmissions required to satisfy offered load G is then $T = \frac{GL}{f\lambda}$. Combining the results of average spatial reuse and expected value of total number of link transmissions T , expected number of slots S required to satisfy G is $\frac{5GLf\lambda}{(l+2f\lambda)^2}$.

Note that for any particular offered load, changing the connectivity among the nodes changes the number of slots required to schedule the transmissions. As shown above, when f increases, total number of required transmissions (T) to satisfy G decreases. On the other hand, spatial reuse also decreases with the increase in value of f . This way, T and the value of spatial reuse determines the required number of slots S . In the above mentioned equation of S , the values of L , l and λ are dependent on node distribution and network area, which in turn shows that required number of slots has a clear dependence on value of the growth factor f .

Fig. 3.2, Fig. 3.3a and Fig. 3.3b show analytical (proven above) and simulated values of throughput capacity, spatial reuse and T respectively. The noticeable difference between the two curves in Fig. 3.2 can be attributed to following two reasons. First, the analytical values derived above attempt to approximate the optimal performance while the simulation results are obtained using greedy scheduler. Second, the above mentioned analysis requires the network to be highly dense for the correct approximation of average path length using $\frac{L}{f\lambda}$. Here, nodes are placed as a 20×20 square grid with offered load being uniform node-to-node traffic. For

Figure 3.2: Performance of links scheduling in grid ($n=400$); Throughput capacity in unit traffic/unit time.

increasing value of growth factor, we apply equal amount of traffic G to the resultant graph. This can be interpreted as transition from Compow graph to DirectTrans graph and capacity at each stage of growth. The data is routed on a shortest path which is closest to the straight line connecting the source and the destination (e.g. straight line routing [90]). For the highest reported value of f in figures, the topology becomes fully connected and growth beyond that has no particular effect.

As can be observed, initial increase in power level of nodes decrements the throughput (number of required slots increase) followed by an increment. This can be characterized as follows - increase in power levels increments the link lengths which in turn decreases spatial reuse T . Decrement in the spatial reuse (Fig. 3.3a) is much more faster than that in T (Fig. 3.3b). So, in this initial region, lower spatial reuse is achieved even when very high number of transmissions are required, increasing the total number of required slots to schedule them. When T also further decreases, this again results in increase of the throughput. Note that even a minor difference between theoretical and simulated values of spatial reuse (or T) can cause significant difference between theoretical and simulated values of S as observed in Fig. 3.2. In the later part (for $13 \leq f \leq 19$ in Fig. 3.2), the throughput capacity in simulation remains unchanged. This is due to the fact that majority of the links at these states of uniform power

(a) Achieved spatial reuse while scheduling T_X

(b) Total number of transmissions required to satisfy G

Figure 3.3: The joint effect of number of transmissions required and achievable spatial reuse determine the throughput capacity

increase are long, high interference links (loner links [118]) which make the spatial reuse to drop to one in almost all slots. Area based formulation fails to capture this behavior which results in monotonous decrease of S in analytical curve during this later region.

Loner Links

In the simulation results, S almost remains unchanged in later part which is due to dominance of *loner links*. If a link can not be scheduled with any other link in the network, it is referred as a loner in its slot. Such links often get created near the center and have very long length which forces the spatial reuse to drop to one. In our contiguous work, we have characterized the length of such links and showed that their existence is independent of the scheduling algorithm since even the optimal scheduler can not achieve spatial reuse of more than one while scheduling a loner link. When power increment of nodes reaches a certain high level ($f \geq 14$), many (upto 70%) of the links become loners. This limits the achievable spatial reuse and causes unvarying behavior of throughput. The analytical curve does not capture this behavior in later part because area-based formulation of spatial reuse fails to capture the loner link behavior. This causes constant decrease in spatial reuse (and T) in analysis while simulated spatial reuse almost becomes constant (approximately 1) due to dominance of loner links.

Further details of loner links and its characteristics were provided in our previous work [118]. It proved that for double disk interference model, loner links have following characteristics:

Lemma 1. *Given a square of side k units, any link of length $0.579k$ or more is loner, and any link of length $0.304k$ is not loner.*

Lemma 2. *Lemma 3.2: Given a circular area of diameter d units, any link of length $0.485d$ or more is loner, and any link of length $0.25d$ or lesser is not loner.*

Upper Bound on Optimal Throughput Capacity

We now compare the simulated throughput of greedy scheduler with upper bound of optimal throughput (lower bound on optimal schedule length) which is derived using conflict graph. A conflict graph is created by placing a vertex for every link of communication graph and an edge between two vertices if corresponding links in communication graph interfere with each other. We use traffic demand of every link in communication graph as the weight of the corresponding vertex in the conflict graph. Now, maximum weight *clique* in the conflict graph is a set of links in communication graph which has maximum total traffic but only one of which can be scheduled in any slot. In most cases, links of nodes near the center (relay hot-spot) form such higher traffic cliques. Since no two links in such a set of mutually interfering links can be scheduled in the same slot, even optimal scheduler requires number of slots which is at least the size of

the clique (in terms of traffic). Numerical results of this upper bound on throughput capacity are presented in Fig. 3.4a. An interesting observation here is that in all cases, greedy scheduler achieves the throughput which is no worse than half the optimal throughput. Also, optimal throughput bound shows a closer resemblance with the analytical throughput curve in Fig. 3.2 which validates the analysis.

Random Topology

Fig. 3.4b shows the throughput results of greedy scheduler for random topologies. Homogeneous Poisson point processes are used to generate random topologies with complete spatial randomness. The Compow range of random node placement is typically higher than that of the grid placement for same number of nodes due to spatial non-uniformity. The simulations are repeated for 30 random topologies and corresponding confidence intervals are presented.

Here, it is interesting to note that in fact Compow and DirectTrans (two extremes of power control) achieve almost equal capacity under uniform N2N load in random topologies. This shows that multi-hop routing on almost minimally connected sparse graph of Compow and direct transmissions in fully-connected DirectTrans topology yield equivalent capacity when links are TDM-scheduled. This is attributed to the interplay of attainable spatial reuse and total number of required transmissions.

3.4.2 Performance Evaluation with CSMA MAC

We now verify the impact of uniform power control when nodes employ CSMA MAC protocol as in IEEE 802.11 standards. To do this, we simulate uniform power control in NS-3 where a total of 50 nodes are deployed uniform randomly on a plane. In each run 12 randomly chosen source and destination nodes communicate. Shortest path routing is used for determining routing paths between source and destination. Radio at each node operates in IEEE 802.11a mode with fixed link rate of 12 Mbps. The results of uniform power increase is shown in Fig. 3.5. A total of 30 runs are used to plot confidence interval with 95%.

The results for both input traffic load shows a similar behavior as in TDMA case. Here, throughput first decreases due to increase in transmission power and interference. This is followed by subsequent increase in throughput which is attributed to shorter (fewer-hop) routing paths. In both cases, the throughput becomes more or less unchanged at very high power levels as it was in TDMA MAC.

3.4.3 Clustered Topology

Most of the real-world topologies actually display some degree of *clusteredness*. They are either highly clustered or fall between random topologies and clustered topologies. We refer to such

(a) Greedy scheduler performs reasonably well compared to the bound on optimal throughput; Throughput capacity in unit traffic/unit time.

(b) Greedy scheduling in random topologies; Throughput capacity in unit traffic/unit time.

Figure 3.4: Comparison with clique-based bound and performance of greedy scheduler in random topologies

Figure 3.5: NS-3 Simulation results of uniform power control with 802.11a nodes

topologies as diffuse clusters. Since the Compow range is the minimum common range such that the nodes are connected, it increases as the topology becomes more and more clustered. This results in higher intra-cluster connectivity but inter-cluster connectivity still remains low. In such case, links providing connectivity between the clusters become traffic bottlenecks under N2N traffic. These links require large number of transmissions and consume large number of time slots when link scheduling is performed. This increases the overall schedule length and reduces the attainable capacity. When power is increased uniformly, new inter-cluster links are added which share the traffic burden and reduces the traffic bottlenecks in the network. This results in higher spatial reuse among the links and overall throughput capacity increases. Increasing power levels of nodes in such case actually has positive effect on throughput. This is surprisingly different from uniform topologies where increasing power levels in N2N traffic had mix effects on throughput.

For study of connectivity, clustering coefficient based on spatial pattern of node distribution is not enough. Instead, we use graph clustering coefficient proposed in [113] which is also known as *transitivity* of a graph. Let $\Delta(v)$ denote number of triangles which have v as one of its three vertices and $\nu(v)$ denote number of triples of vertex v . A *triple* is a connected subgraph which has three vertices but only two edges. A triple belongs to a vertex v if v is the vertex which has

Figure 3.6: Topology transitivity can be used to understand and predict the impact of power control on network's throughput capacity ($n \approx 400$); Throughput capacity in unit traffic/unit time.

both edges incident to it. Now, number of triangles in graph G , $\Delta(G) = 1/3 \sum_{v \in V} \Delta(v)$ while number of triples in graph G , $\nu(G) = \sum_{v \in V} \nu(v)$. Then transitivity of the graph G is defined as:

$$\tau(G) = \frac{3\Delta(G)}{\nu(G)} \quad (3.1)$$

Thus, transitivity ($0 \leq \tau(G) \leq 1$) can be interpreted as likelihood that any two neighbors of a node are connected. As an example, for a given set of points, a spanning tree has transitivity of 0 while complete graph has transitivity of 1. It can be seen that if the Compow range of set of points is relatively high, the Compow graph of points is expected to have higher transitivity. Note that Compow graph is a unique graph for any particular set of points. Compow graphs of several point patterns have following τ values (approximately): perfect square grid - 0, perturbed square grid - 0.2, square grid with diagonal - 0.44, Poisson random - 0.6, diffuse clusters - 0.7-0.8 and clustered - 0.9.

Transitivity of any Compow graph shows an interesting relation with how throughput changes when power is increased uniformly. This is shown in Fig. 3.6. We simulate clusters of different intensities using Matérn cluster process [78]. Results are presented using greedy

scheduler with 400 nodes deployed on a unit square. Throughput changes its behavior differently as transitivity increases from a perfect grid to clustered topologies. In topologies which have transitivity similar to diffuse cluster or more, in fact increasing power levels always results in better throughput. Clique based upper bound of optimal scheduler also follows the same behavior, results of which we do not show for brevity. This shows that for the same traffic pattern (node-to-node uniform), uniform random topology and clustered topology results in different throughput behavior with change in power levels. *This is a practically useful result since it shows that increasing power levels of nodes results in better throughput capacity when the nodes are clustered. Also, for a given set of nodes, transitivity of the Compow graph can be calculated and then it is possible to predict the behavior of throughput with increase of power levels.*

3.5 Uniform Node-to-gateway (N2G) Traffic

Now, we analyze a more commonly used and practically important traffic pattern which is N2G traffic. The most representative use of such traffic pattern is observed in Wireless Mesh Networks (WMNs) in which all nodes send traffic to one or more gateway nodes which forwards it further to the Internet. In one of the most useful results about capacity of WMNs, [83] proved that per node throughput in WMNs can not be more than $O(1/n)$ which is significantly worse than classical result of $O(1/\sqrt{n})$ presented in [74]. This is because traffic of every node, no matter how many hops away it is from the gateway, has to ultimately traverse through the bottleneck links connecting to the gateway. Per node throughput of $O(1/n)$ is also achievable in WLANs, but it has been empirically observed that WMNs often achieve even worse throughput than WLANs (often by a factor 2 or 3).

We show that WMNs in fact achieve per node throughput of $O(1/\delta n)$, where $\delta \geq 1$ is a factor dependent on the hop-radius of the network graph. Here, *hop-radius* is defined as length of the longest path from a node to the gateway assuming that the gateway has the least eccentricity among all nodes. The result pertains to networks where interference model is based on the distance. Below we present the analysis for achievable per node throughput in WMNs with bi-directional protocol interference model (as described in Sec. 3.3). We then go on and show how this throughput capacity is dependent on the power assignment.

3.5.1 Capacity Analysis

As before, let λ denote the Compow range, and power levels of all nodes are incremented using the growth factor f resulting in communication range of $f\lambda$ at every node. Let R denote the hop-radius of the network graph. Let tier t be a set of nodes that are t hops away from the

Figure 3.7: Activity on a link in 1st tier affects all links of 1st and 2nd tier and many links of 3rd tier

gateway and hence R is also the number of tiers in the network. With assumptions of uniform and dense distribution of nodes, number of tiers in the network $R \approx \frac{R_N}{f\lambda}$ where R_N is the Euclidean radius of circular network area in consideration. Now, number of nodes in any tier i can be given as :

$$n_i = \frac{(2i - 1)n}{R^2} \quad (3.2)$$

Every node in the network sends p packets to the gateway during the time frame under consideration. For simplicity of analysis, a link can be associated with the tier of its source node. Links of any tier i forward traffic for all nodes at tier $i + 1 \dots R$ as well as traffic of nodes at its own tier. It can be assumed that shortest paths to the gateway always contain links which forwards traffic between the tiers. With the assumption of uniform density of nodes, load on all links in tier i is:

$$\begin{aligned}
L_i &= p \cdot \left(n - \sum_{j=1}^{i-1} n_j \right) \\
&= p \cdot \frac{n(R^2 - (i-1)^2)}{R^2}
\end{aligned} \tag{3.3}$$

Bottleneck Collision Domain (BCD) is defined as set of mutually interfering links in which no more than one link can be scheduled in same slot and cumulatively they have to transmit maximum total traffic.

It is easy to see that in WMNs, such a BCD is often created near the gateway node. As shown in Fig. 3.7, when a link in first tier is scheduled, almost all links in second and third tiers suffer from interference and can not be scheduled concurrently. For the worst case performance analysis, we consider that all links of first three tiers are part of single BCD. This can be a really pessimistic consideration of interference since it might be possible to schedule two links concurrently in third tier which are on opposite sides each other (Fig. 3.7). We will discuss later how considering the links of only first two tiers in BCD can be too optimistic. The size of BCD ($|BCD|$) is defined as total amount of traffic its links have to transmit which can be calculated as:

$$\begin{aligned}
|BCD| &= L_1 + L_2 + L_3 \\
&= p \cdot n + p \cdot n \left(\frac{R^2 - 1}{R^2} \right) + p \cdot n \left(\frac{R^2 - 4}{R^2} \right) \\
&= p \cdot n \left(\frac{3R^2 - 5}{R^2} \right)
\end{aligned} \tag{3.4}$$

By definition of BCD, total network traffic np requires at least $|BCD|$ number of slots. Hence, network throughput can not be more than $\frac{np}{|BCD|}$ and with assumption of absolute fairness, per node throughput can not be more than $\frac{p}{|BCD|}$. Combining this with (4), per node throughput can not be more than $1/\delta n$ where $\delta = \frac{3R^2 - 5}{R^2}$. Hence, it is shown that per node throughput in WMNs is $O(1/\delta n)$ where δ is a factor which depends on number of tiers in the network.

When $R = 2$, every node can achieve throughput of $\frac{p}{|BCD|}$ where $|BCD| = L_1 + L_2 = p \cdot n \left(\frac{2R^2 - 1}{R^2} \right)$. Since $R = 2$, $\delta = \left(\frac{2R^2 - 1}{R^2} \right) = 1.75$. Similarly, it can be shown that when $R = 1$, $|BCD| = L_1 = p \cdot n$ and fraction $\delta = 1$. This results in $O(1/n)$ where every node can directly reach gateway similar to the WLAN case.

Surprisingly, factor δ converges to 3 as $R \rightarrow \infty$ in (4). *This suggests that no matter how large the hop-radius of the network becomes, WMNs can still achieve one third of the capacity of WLANs even in the worst case.* This is due to the fact that at least one link in first three tiers can always be scheduled in almost all slots. It is important to note that the value to which the δ converges also depends on how BCD is calculated, which in turn is dependent on the interference model under consideration.

Numerical Evaluation

In node-to-gateway uniform traffic pattern, greedy scheduler performs near-optimal because almost all links away from the gateway (beyond first three tiers) can be almost always be scheduled in parallel with links of first three tiers (BCD). Hence, number of slot required $S \approx |BCD|$. This is verified by comparing the performance of greedy scheduler and upper bound of optimal throughput (Fig. 3.8a). Similarly, Fig. 3.8b verifies simulated throughput with analytical result of $O(1/\delta n)$. For simulations, 1000 nodes are randomly placed on a unit-disk with the gateway placed at the origin. For achieving continuous values of throughput points, we assume hop-radius $R = \frac{R_N}{f\lambda}$ to be continuous also. As the hop-radius of the network increases network throughput drops from 1 and converges to 0.33 for large values of radius. It is noticeable that even when radius increases from 1 to 2, network throughput drops significantly (by a factor $\delta = 1.75$). We have also verified the convergence of δ to 3 for extremely high values of network radius (in scale of thousands).

The minor difference between the analytical and simulated curve can be attributed to the fact that average spatial reuse in first three tiers is often slightly larger than 1. This is in line with our rather pessimistic analysis which assumed that only one link can be scheduled in first three tiers. If it would have been assumed that only one link can be scheduled in first *two* tiers, analytical value of throughput would have converged to 0.5 (as shown in Fig. 3.8b) which would have been clearly too optimistic when compared to actual simulated results.

The analysis shows clear dependence of δ on R which in turn dependent on Euclidean network radius R_N , Compow range λ and growth factor f . Since R_N and λ are dependent on network deployment area and node distribution, growth factor f is the only control parameter of interest. Dependence on f shows that increase of f results in smaller network hop-radius R which reduces factor δ , resulting in actual increase of throughput. *This suggests that it is always better to increase power level of nodes which decreases the network hop-radius and increases the throughput. This is a useful capacity result especially in case of WMNs since it proves that reducing worst case hop distance to gateway always performs better in terms of throughput.* This is also true when multiple gateways are utilized in a WMN as shown next.

(a) Greedy scheduler performs near optimally in WMNs; Throughput capacity in unit traffic/unit time.

(b) Relation of Throughput and hop-radius in WMNs; Throughput capacity in unit traffic/unit time.

Figure 3.8: Comparison of simulation results and theoretical estimate

3.5.2 Multiple Gateways

In large metro-scale WMNs, having one gateway is not scalable and sufficient to meet the demand. When more and more nodes are assigned the role of gateway, network throughput increases but associated cost also increases since such gateway nodes typically have a high-speed fiber link or a satellite connection. In such case, objective of network designer is to achieve as much throughput as possible with fewer gateways. We saw that increasing power level of nodes results in better throughput in one gateway case. In this section, we show that this is also true for multiple gateways and in fact power control can be used to achieve better throughput with fewer gateways.

The problem of placing k gateways in the network can be formulated as facility location problem or problem of finding k -medians of network graph. Since these problems are known to be NP-hard, we use simple yet efficient heuristics to place the gateways. In uniform random topologies, square network area is divided into a grid and the nodes nearest to the grid intersection points are assigned the role of gateways. Such a placement allows each node to equally share the gateway capacity when every node forwards its data to the nearest gateway using shortest paths. Also, number of nodes which send data to each gateway is almost equal, resulting in fair load balancing among gateways. We simulate the scenario using 2500 randomly distributed nodes with number of gateways increasing from 1 to 100. As before, power control is used to increase the transmission range of nodes by factor of f and greedy scheduler is used to schedule the link transmissions. Fig. 3.9a shows impact on throughput with different values of f when number of gateways in the network are increased. As can be seen, when nodes double their transmission range, on an average 20% more throughput can be achieved for any given number of gateways. This is a cost-effective solution since better throughput can be achieved with fewer gateways when nodes increase their power levels. After a certain value of f ($f \geq 3$ in our scenario), power control advantages become insignificant since at higher power levels, BCD of different gateways start overlapping with each other. Such value of f is still very high when Compow range is relatively smaller compared to network span and there is enough opportunity to increase power levels in such cases.

Grid-based gateway placement can not be used in non-uniform clustered topologies because only few of the grid intersection points may actually lie within the clusters. For different topologies, same grid placement might result in different number of gateways. Instead we use a simple heuristic where k gateways are equally divided into clusters which are then randomly chosen in each cluster. We simulate the scenario using 300 nodes where number of gateways are increased from 1 to 30. Fig. 3.9b shows that even in case of non-uniform topologies, increasing power level of nodes results in upto 15% throughput improvement. Since optimal gateway placement would result in better load balancing among gateways than random placement, power control advan-

(a) Uniform topologies ($n=2500$); Throughput capacity in unit traffic/unit time.

(b) Clustered topologies ($n=300$); Throughput capacity in unit traffic/unit time.

Figure 3.9: Power control in WMNs with multiple gateways

tages are likely to be more because better spatial reuse can be achieved among the bottleneck links near the gateways.

3.6 Concluding Remarks

In this chapter, we investigated impact of uniform power control on throughput capacity in different traffic patterns and topologies. We showed that when the links are TDM-scheduled, increasing power levels of nodes results in increased throughput in case of many representative topologies (e.g. clustered) and traffic patterns (e.g. N2G traffic).

In random topologies with N2N traffic, low power Compow and high power DirectTrans both attain the same throughput capacity. As the clusteredness of the topologies increase, increasing power levels of nodes always results in better throughput. Also, increasing power levels of nodes increases the throughput capacity in node-to-gateway traffic pattern.

Chapter 4

Hot-spot Mitigation using Centrality-based Power Control

In the previous chapter, we saw that uniform power control has significant impact on network throughput capacity. The complex interaction of various factors determines the actual throughput capacity, and we outlined these factors in the previous chapter. In this chapter, we address the problem of disproportionate relaying among nodes of wireless network.

When shortest path routing is employed in large scale multi-hop wireless networks, nodes located near the center of the network have to perform a disproportionate amount of relaying for others. Nodes in such traffic hot-spots deplete their batteries faster than others due to their high relay load. These traffic hot-spots also adversely affect the network capacity due to increased congestion in the regions. To solve the problem, various divergent routing schemes are used which route the data on center-avoiding divergent routing paths. Though they achieve better load balancing, overall relaying is increased significantly due to their longer routing paths.

In this chapter, we propose power control as a way for balancing relay load and mitigating hot-spots in wireless networks. Using a heuristic based on the concept of *centrality*, we show that if we increase the power levels of only the nodes which are expected to relay more packets, significant relay load balancing can be achieved even with shortest path routing. In contrast to divergent routing schemes, such load balancing strategy is applicable to any arbitrary topology and traffic pattern. With extensive simulations, we show that centrality based power control can drastically increase the network lifetime of sensor networks. We compare its performance with other divergent routing schemes and multiple battery level assignment strategies. Also, it is shown that centrality based power control results in better throughput capacity in many topologies.

4.1 Problem Description

Many of the routing protocols proposed for multi-hop wireless networks such as wireless mesh networks depend on shortest path routing (SPR) due to its characteristics of simplicity, robustness and scalability. It has been observed that when hop count based shortest path routing (SPR) is used for uniform node-to-node communications in a multi-hop network, certain nodes have to perform disproportionate relaying of data for others. Such *hot-spots* are often created near the center in uniform topologies and also at cluster peripheries in clustered topologies. This increased congestion in certain areas has shown to be resulting in reduced network capacity. When the nodes are energy constrained as in sensor networks, nodes performing more relaying than others deplete their batteries faster, reducing the overall network lifetime. As an example, when traffic flows between random source and destination pairs, network lifetime is often bounded by the lifetime of the nodes near the center since majority of the end-to-end shortest paths pass through them. On the other hand, when nodes send their data to a central entity (a sink or a gateway), generally one hop neighbors of the sink have to perform the most relaying which results in earlier depletion of their batteries [101], followed by disconnection of the sink from other alive nodes. In most cases, relay load distribution of nodes is significantly unfair where some nodes exhaust their batteries very quickly while others have not consumed even half of their energy resource.

Divergent Routing Schemes

The problem of disproportionate relaying has been addressed mainly by devising routing strategies in which routing paths intentionally try to avoid passing via center. Curved paths in curve-ball routing [125, 95], one-turn rectilinear paths in Manhattan routing [137] and edge reflection paths of outer space routing [106] are some examples of such strategies. We refer to such center-avoidance routing strategies generally as *divergent* routing. Any such divergent routing scheme increases relaying load of the nodes near the periphery of the network while taking away some relaying burden from the nodes around the center. This results in better overall load balancing. This advantage comes at a cost of various other sacrifices. Most of the divergent routing schemes depend on geometrical properties of the network (for mapping the network over symmetric space like torus or sphere) which limits their applicability to uniform topologies only. Routing paths in any such scheme are also longer (higher stretch factor) when compared to shortest routing paths. Moreover, divergent routing schemes sacrifice the fundamental advantages of SPR such as robustness, scalability and simplicity. In many cases, divergent routing schemes do not eliminate the hot-spots in the network because the relay load of the nodes near the center decreases moderately while the load on nodes around the periphery increases significantly. This results in only a moderate increase of lifetime of network since the relay load is not completely balanced

among nodes. This raises an interesting question – is it possible to preserve SPR (and all its advantages) while achieving better relay load balancing?

Load balancing Through Power Control

One of the assumptions in divergent routing schemes is that all nodes operate at Compow [111] power level and routing is performed on the resultant topology. In Compow, all nodes use a uniform power level which is minimum required to maintain network connectivity. Compow achieves better concurrency in link scheduling due to lesser interference but requires more relaying at nodes because of longer routing paths. This motivates the following questions which are central to our work – is disproportional relay load distribution in multi-hop communications also a consequence of Compow power range together with SPR? And can it be dealt with using power control instead of modifying routing?

Figure 4.1: General nature of path and relay load characteristics

In this chapter, we propose power control as a way to balance relay load in wireless networks.

We show that if the communication range of nodes are properly increased by increasing their power levels, better relay load balancing can be achieved even when routing on the shortest paths. In all cases, choosing only a small subset of nodes and increasing their power levels is sufficient to achieve load balancing that is significantly better than divergent routing schemes. The fundamental advantage of such power control based load balancing is that it preserves all the benefits of shortest path routing and still achieves a significant relay load balancing. Because all the characteristics of shortest path routing is retained, such load balancing can be applied to any kind of arbitrary topologies (e.g. clustered) and traffic patterns (e.g. node-to-gateway) where divergent routing can not be applied.

The proposed load balancing scheme does not route the data on divergent routes to avoid passing through the nodes near the center. Instead, the data is routed on the shortest paths only and the nodes which are expected to relay more packets for others are skipped or *jumped over*. In the case of uniform topologies, this results in longer hops being taken near the center which reduces the relay load burden of congested nodes without increasing the relay load of the nodes on the periphery. Power control based load balancing presented here assigns higher power levels to nodes which are expected to relay more packets. This has an underlying requirement of estimating the relay load of nodes in advance so that communication range can be assigned to them accordingly. We calculate *betweenness* centrality of nodes which assigns every node a score based on their expected relay load. The centrality value is then used to assign every node a power level which is proportional to its expected relay load. This increases the connectivity of the nodes who were expected to relay more packets previously. When shortest paths between nodes are found in this new more connected network, they pass over congested nodes, producing better load balancing.

Since the relay load is better balanced among the nodes with actual reduction in overall relaying, the overall network lifetime is improved using centrality based power control. Note that longer hops in routing paths can only be achieved by controlling the communication range of nodes using power control. However, the cost of relay load balancing is the higher power that must be expended in these transmissions, and hence higher energy expenditure. It may appear at first that since some nodes are performing high power transmissions, the overall energy expenditure might increase with centrality based power control. Surprisingly, the proposed scheme achieves an intelligent balance between the transmission power level assigned to every node and its corresponding relay load. This also guarantees an improved balance of energy expenditure among the nodes because the power assignment itself is performed using the predicted relay load. We show that improved relay load balancing, reduced overall relaying and evenly distributed energy expenditure increases the network lifetime of sensor networks dramatically. The numerical results show on an average 30% increase in network lifetime when compared to divergent routing schemes.

One of the other disadvantages of the divergent routing schemes is that there is a trade-off [65, 96] between length of the routing paths (path-stretch) and amount of load balancing achieved. We show that power control based load balancing does not show such a trade-off with path stretch. Instead, it is observed that load balancing and capacity sometimes show a trade-off when power control based load balancing is applied in some of the topologies. We characterize that such a trade-off is limited to the case of uniform node placement and as the node placement becomes more random and clustered, increased capacity can be achieved together with better relay load balancing.

4.2 Network Model and Preliminaries

We model the network using a directed graph $G = (V, E, r)$, where V is a set of n stationary nodes and r is a set of communication range values assigned to each node in V . There exists an edge from node u to node v if their Euclidean distance $d_{uv} \leq r_u$. This allows the modeling of variable power control where each node might have a different communication range. Note that when the value of r_v is same for all $v \in V$, the resultant network graph can be considered as an undirected graph (unit disk graph) since all the edges are bidirectional. In one such case, when there is no explicit power control, all nodes are assumed to be operating at Compow power level. Compow range (r_{min}) where $r_v = r_{min}, \forall v \in V$ is defined as minimum value of common range such that G is connected. We refer to the Compow graph as G_C . We have proved that r_{min} is the value of maximum edge weight in a Euclidean minimum spanning tree of V (also asserted, but without proof, in [138, 123]). The complete proof is presented in Appendix A; this result allows us to efficiently determine r_{min} for large set of nodes using any known polynomial time algorithm.

Centrality values of all nodes are determined from the Compow graph and are used to assign different power levels to different nodes. Here, an increase in power level of a node can actually be interpreted as upper constraint placed on the transmission power level of the node. That is, if a node is assigned a specific power level, this does not mean that it will always transmit at that power level. If a neighbor is reachable at a lower power level, it will utilize that to communicate with it. In this case, each node uses power just sufficient to provide the range to the destination node of each transmission, but cannot exceed the “assigned power level”. Thus some nodes are out of range at any assigned level, but more nodes become available at higher levels. All the schemes presented in the work along with the proposed scheme take advantage of this power control policy. We use path loss model of signal propagation. If transmitted signal power is P_t and distance between the transmitter and the receiver is d then received signal power (P_r) attenuates as $P_r \propto P_t(d^{-\alpha})$, where α is the path loss exponent which depends on environment ($2 \leq \alpha \leq 5$). Let β be the receiver sensitivity threshold such that signal is properly decoded

at the receiver if $P_r \geq \beta$. For a node transmitting at power P_t , the communication range is the distance at which $P_r = \beta$ in absence of any other interference. Now, power level of nodes can be presented in terms of their communication range. As an example, in G_C all nodes are operating at power level $P(r_{min})$ which is necessary and sufficient to achieve communication range of r_{min} at all nodes. Now, if a node wants to increase its communication range by a factor of f , it tunes its power level to $P(f \cdot r_{min})$. This way, increase of power levels are normalized to the Compow range r_{min} , not to Compow power level $P(r_{min})$ because $P(f \cdot r_{min}) \neq f \cdot P(r_{min})$ necessarily.

Two widely used traffic patterns which we used in last chapter namely, *uniform node-to-node* and *uniform node-to-sink* are studied in this chapter. In uniform node-to-node traffic, every pair of source and destination communicate with amount of traffic which is uniform across all such pairs. Such traffic pattern is commonly used in applications like querying and storing data within the network [98, 142, 73], and target tracking [53, 36, 38, 124, 126] in military sensor networks. In uniform node-to-sink traffic, all nodes send uniform amount of traffic to the sink only. Habitat monitoring, environment observation and structure health monitoring [159] are some of the applications where such a traffic pattern is commonly utilized. We assume that the nodes are stationary and there is no consideration of mobility in this work. Note that the presented work relates to the throughput capacity of the network, and is not dependent on what application uses that capacity. The results obtained here are most useful for applications in which the traffic being generated by each node is more or less constant, as in many sensor network as well as mesh networks. Without loss of generality, we also assume that all nodes operate on the same channel.

4.3 Modeling Relay Load

Conceptual difference between load balancing using divergent routing and power control is depicted in Fig 4.1. It can be observed that divergent routing schemes (Fig. 4.1c, 4.1d) transfers much of the relay burden onto the nodes around the periphery. In power control based load balancing (Fig. 4.1e, 4.1f), data is forwarded on shortest path only but nodes in hot-spot regions are skipped or *jumped over*. This results in longer hops taken near the center hot-spot in uniform topologies. To achieve such longer hops, nodes which are expected to relay more packets should be assigned high power levels and larger communication range. If the relay load at every node can be estimated, then a node can be assigned power levels proportional to its estimated load. This increases the connectivity of the nodes which were likely to relay more packets previously. When shortest paths between nodes are found in this new more connected network, they pass over congested nodes, producing better load balancing. The mentioned heuristic has an underlying requirement for accurately estimating the relay probability of nodes for any given topology

which we discuss next.

Techniques for modeling and estimating relay load have been limited to uniform topologies with assumptions like continuous density of nodes. One of the first few such approaches was presented in [125] where relay load probability of a node was derived as a function of its (Euclidean) distance from the center of the network, when routing over the shortest paths between the nodes. It is possible to show that nodes at the same distance from the center can have different relay load if the topology is even slightly non-uniform. Similarly, [90] presented a Voronoi cell-based technique in which it was shown that relay load of a node is a function of perimeter of its Voronoi cell, its location in the network and the traffic pattern in consideration. Even with assumptions of uniform node-to-node traffic pattern and node distribution, Voronoi tessellation based model might not always be sufficient because nodes adjacent to each other in network graph might not always have neighboring Voronoi cells. Such techniques do not always accurately estimate the relay load because they rely on geometrical properties of the network and not the underlying network connectivity.

4.3.1 Betweenness Centrality

We are interested in devising a relay load estimation technique which relies on properties of network graph. Centrality indices [44] proposed for analysis of large network assign relative importance or status to every node in the network based on certain characteristic of interest. One such centrality named betweenness [62] of a node depends on how many end-to-end shortest paths between other nodes of network actually pass through it. In node-to-node uniform traffic, a node is likely relay more data for others if it falls on relatively more shortest paths between other nodes. For a network graph G , if S_{xy} is number of shortest paths between vertices x and y and $S_{xy}(v)$ denotes number of shortest paths between x and y which pass through vertex v , then betweenness centrality of v (denoted by $b(v)$) is

$$b(v) = \sum_{x \neq y \neq v \in V} \frac{S_{xy}(v)}{S_{xy}} \quad (4.1)$$

The fraction in (4.1) (also known as *pair-dependency*) can be interpreted as the probability that vertex v will be relaying data between vertices x and y . Betweenness centrality of a node can be regarded as measure of how important a node is in carrying out relaying of data for other nodes.

Betweenness centrality is a structural index of the graph, that is if H is isomorphic to G ($G \simeq H$), then betweenness centrality satisfies the condition: $\forall v \in V : G \simeq H \Rightarrow b_G(v) = b_H(\phi(v))$. Also, betweenness of nodes change considerably with changes in the edge set of network graph which may require frequent recalculations. This is not a concern here since we do not consider

Figure 4.2: Comparison of simulated relay load of nodes and their centrality values in Compow graph and Delaunay graph (all normalized with maximum value, $n=400$ randomly distributed in unit square); Y-axis in first plot shows relay load in number of packets, Y-axis in second and third plots show betweenness centrality values.

any mobility of nodes. As described in [44], straightforward usage of Dijkstra's algorithm for computing betweenness of nodes can have running time of $O(n^3)$. Brandes's algorithm [43] can compute betweenness of all nodes in $O(nm)$ time for unweighted graphs and $O(nm + n^2 \log n)$ for weighted graphs, where m is number of edges in the graph. In terms of n , this does not impose significant computational cost for moderate to large sized networks (400-1000 nodes). While in terms of m , as it is described below, betweenness centrality is required to be determined in the Compow graph which is a relatively sparser graph ($m \ll n(n-1)$). When considering clustered topologies, intra-cluster connectivity can be much higher even in COMPOW graphs which can make m large. In such cases, Delaunay triangulation can be used for generation of a sparser graph and calculation of betweenness centrality indices. This can significantly reduce the value of m and can still maintain a bounded stretch of shortest paths (no more than a stretch of $\frac{2\pi}{3 \cos(\pi/6)}$ in geometric graphs [85]). Fig.4.2 shows betweenness centrality of nodes in Compow graph and Delaunay graph, and compares it with their actual simulated relay load in Compow graph when employing uniform node-to-node traffic pattern and SPR.

4.4 Centrality-based Power Control

Following steps describe how betweenness indices are used to assign power levels to nodes.

1. For a given V , first determine the Compow range (r_{min}) and create $G_C = (V, E_C, r_{min})$.
2. Calculate betweenness centrality of all nodes in G_C using Brandes's algorithm and are normalized using $\max\{b(v) \mid v \in V\}$.
3. Every node $v \in V$ is assigned a power level (P_v) as: $P_v = P(D_{min} + (b(v) \cdot (D_{max} - D_{min})))$ where $D_{min} \geq r_{min}$ to guarantee connectivity and $D_{max} \geq D_{min}$. Even if $D_{max} = D_{min} = r_{min}$, resultant graph is at least G_C .

Any such assignment is uniquely referred as $\psi(D_{min}, D_{max})$ and resultant more connected graph of betweenness centrality based power assignment is called G_B . We set $D_{min} = r_{min}$ and vary $D_{max} = f \cdot r_{min}$ using a factor $f \geq 1$. Here, D_{min} and D_{max} are dependent on r_{min} which is a property of V , only control parameter is f which we refer as *growth factor*. For any reasonable value of f , ψ results in increased power levels and communication range of nodes which were expected to relay more packets. Nodes near the center in uniform topologies have higher betweenness and are assigned higher power levels. As shown in Fig. 4.1f, this allows them to *jump over* other nearby congested neighbors. If a source and a destination are on opposite side of each other over the periphery, packet from source first starts progressing along shorter hops. As it reaches near the center, long-distance transmissions occur which results in longer hops, followed by fewer shorter hops at the end. This results in subsequent reduction of relay load of nodes near the center without increasing relay burden on nodes on periphery.

4.4.1 Advantages of Load Balancing Through Power Control

Foremost advantage of such load balancing using power assignment is that it can be applied to any kind of arbitrary topology like clustered where divergent routing mechanisms can not be applied. Also, centrality measure of nodes can be calculated for any specific set of shortest paths pertaining to traffic pattern of interest, which makes the mechanism applicable for load balancing in any other traffic patterns (e.g. node-to-sink uniform). The complexity of the scheme is dominated by the complexity of centrality algorithm, and Brandes's algorithm performs well even with moderately large networks as we saw above. The presented scheme is static and centrality calculation is necessary only once. The only necessary requirement of the scheme is that the nodes should be able to vary their power levels as per the centrality based calculations. Note that the proposed power control is centralized and its distributed extensions are discussed in future work.

Figure 4.3: Relay load of nodes and effect of growth factor on load balancing in a 20x20 grid with node-to-node uniform traffic; Y-axis show relay load in number of packets.

Fig. 4.3 shows the relay load of nodes (in number of packets) when centrality based power assignment is used for load balancing. It shows the impact of growth factor on load balancing in a 20 x 20 grid network. As discussed before, D_{min} is set to r_{min} and $D_{max} = f \cdot r_{min}$. Initially, when $f = 1$, $D_{max} = D_{min}$ and resultant topology is a Compow graph of V . In such case, there is no explicit effect of centrality values because growth factor is set to 1 and relay load distribution displays hot-spots near the center. When growth factor increases, the actual difference between maximum and minimum power level assigned in the network also increases. This results in higher power levels and communication ranges for nodes which have higher betweenness centrality and are expected to relay more packets. As can be observed in Fig. 4.3, central nodes are now assigned higher power levels which results in better load balancing. The growth factor f is a tunable parameter here and its value can be decided based on several factor which we discuss later.

4.4.2 Analysis of Load Balancing Ratio

The load balancing achieved by the centrality based power control depends on the value of the growth factor. Increasing the growth factor also increases the connectivity among the nodes. The relation between the load balancing and connectivity was first established by [65]. To

further generalize, let H be a graph where betweenness centrality of nodes are found, and let G be the resultant graph once the power assignment $\psi(D_{min}, D_{max})$ is applied. It is easy to see that edge set $E_H \subseteq E_G$ and H is a spanner of G . Let dm_G and dm_H denote the diameter of G and H respectively. In fact, H is referred as σ -spanner of G where $\sigma = dm_H/dm_G$ is called the stretch factor of H .

Now, let us assume that there exist an optimal load balancing routing strategy and $l^{\mathcal{R}}(u)$ denotes relay load imposed on node u by the optimal load balancing routing of traffic demand set $\mathcal{R}$ in a network. Let $l^{\mathcal{R}}(G) = \max\{l^{\mathcal{R}}(u) \mid u \in V\}$ and *load balancing ratio* for two different connected graphs H and G defined on the same point set V is $l^{\mathcal{R}}(H)/l^{\mathcal{R}}(G)$. [65] proved the following relationship between the stretch factor and the load balancing ratio.

If H is σ -spanner of G then for a given request set $\mathcal{R}$ and optimal load balancing routing, $l^{\mathcal{R}}(G)/l^{\mathcal{R}}(H) = O(1/\sigma^2)$.

This further formalizes the fact that increasing the value of the growth factor f decreases the diameter of G which in turn increases the stretch factor σ . This results in improved load balancing in G as compared to that of its spanner H . Note that this is proven for an optimal load balancing routing scheme, not the shortest path routing which is central to this work. We demonstrate via simulation results (presented in Section 4.5) that in the set of representative topologies we study here, it is indeed true that increasing the growth factor f results in improved load balancing.

4.4.3 Impact on Energy Efficiency

The centrality based load balancing mechanism increases connectivity between the nodes in the regions which were previously congested. As in Fig. 4.3 where $f=4$, nodes near the central hot-spot are assigned high communication range which results in reduced overall relaying in the area. It might appear at first that since some nodes in centrality based power control are transmitting at higher power levels and may deplete their batteries faster than other. But in fact number of transmissions required by such nodes are reduced significantly. Centrality based power control tries to achieve a balance between the nodes which have to transmit more number of times but with lower power levels and the nodes having to transmit at higher power levels but fewer times. The increase in energy expenditure for any given node is more than offset by the reduction in the transmission load of that node. This way, appropriate balance is achieved between actual amount of relaying and power level of nodes due to proper utilization of their betweenness values.

Apart from better load balancing, centrality based power control reduces the overall energy consumption because of reduction in total number of required transmissions and receptions. Reception is also a significant reason of power consumption in wireless sensor networks. It was

shown in [154] that routing on shortest paths with least number of hops is almost always more energy efficient. When all nodes are operating at Compow power level, connectivity among the nodes are lesser than when they operate on centrality based power levels. So, shortest paths in topology resulting from centrality based power control will have fewer hops than shortest paths of Compow topology. This way, when routing uniform node-to-node traffic on shortest paths, centrality based power control requires fewer transmissions/receptions than Compow power control mechanism, which in turn results in lower overall power consumption.

Centrality based power control mechanism with shortest paths is also more energy efficient than divergent routing scheme with Compow power levels. Any divergent routing scheme of load balancing results in longer routing paths (more hops) when compared to shortest paths. This is typically measured using *average path stretch* of a routing scheme which can be defined as average ratio of hop-length of routing paths in a divergent routing scheme to hop-length of shortest routing paths. The path stretch and load balancing ratio display a trade-off ([65], [96]) in any divergent routing scheme which makes better load balancing with lower stretch factor inherently difficult. Hence, load balancing improves with increased path stretch which results in increased path lengths and more transmissions and receptions. As an example, it was shown in [106] that outer space routing consumes 1.4 times more energy than shortest path routing. Hence, in general case, divergent routing scheme would end up spending more energy than shortest path routing.

Collectively, centrality based power control mechanism reduces overall energy consumption when compared to divergent routing schemes. Also, the energy expenditure of nodes is also more uniform. This results in drastic overall increase of network lifetime of sensor networks.

4.5 Numerical Evaluation

Three sets of simulation results are presented to confirm the claims of load balancing using centrality-based power control. In the first set, load balancing strategy is applied to different kinds of topologies of sensor networks. We also compare its load balancing performance to existing divergent routing schemes. Next, we show how the load balancing affects the attainable capacity in different topologies. At the end, we present energy-efficiency and network lifetime results for sensor networks.

4.5.1 Load Balancing

Fig. 4.4a shows the relay load of nodes resulted using SPR in G_C and centrality based more connected graph G_B . We use 20×20 grid and set the growth factor $f = 6$. That is, if $b(v)$ was the betweenness centrality of a node v , operating at power level $P(r_{min})$ in G_C , in G_B ,

it is assigned power level $P_v = P(r_{min} + b(v) \cdot ((6 * r_{min}) - (r_{min})))$. As expected, relay load distribution in G_C clearly shows hot-spots near the center. In G_B , even with shortest path routing, relay load is very well distributed among nodes.

Next, we analyze the effect of growth factor on load balancing achieved by $\psi(D_{min}, D_{max})$ power control. We consider grid (Fig. 4.4b), random (Fig. 4.5a) and clustered topologies (Fig. 4.5b). Random topologies ($n \approx 400$) are modeled as homogeneous Poisson point processes while clustered topologies ($n \approx 300$) are generated using Matérn cluster process [78]. Shortest path routing is used with node-to-node uniform traffic pattern. In all cases, D_{max} is varied by the growth factor f using $D_{max} = f * r_{min}$ and D_{min} is set to r_{min} . Whenever random topologies are considered, results are presented for 30 instances of random topology with 95% confidence interval. Here relay load is defined as number of packets a node has to relay for other nodes. It is observed that even for small growth factor, relay load balancing improves significantly in all topologies. Though initial decrease in maximum, average and standard deviation of relay load is more significant, it consistently decreases with higher values of f . In clustered topologies, nodes providing inter-cluster connectivity become traffic bottlenecks and resultant relay load distribution can be highly disproportionate. Divergent routing based load balancing schemes are not applicable in such clustered topologies. As can be observed, ψ achieves significantly better relay load balancing in clustered topologies even for very small values of f .

Now, we compare the ψ with other well-known divergent routing schemes. Load balancing of shortest path routing in centrality based power controlled topology (G_B) is compared with the load balancing of shortest path routing in Compow topology (G_C), and three well-known divergent routing schemes, namely outer space routing [106], Manhattan routing [137] and curve-ball routing [125]. In outer space routing, packets are first forwarded towards the periphery of the network and is then reflected back from some intermediate node towards the actual destination. In Manhattan one-turn routing, source forwards the packet to an intermediate node which is near the intersection of horizontal/vertical lines passing through the source and destination. In curve-ball routing, network plane is first mapped on a sphere and shortest paths on sphere are then mapped back to the plane. This results in center-avoiding curved routing paths. All divergent routing schemes are also employed in G_C .

Fig.4.6a shows the results of load balancing in a 400 nodes network and uniform node-to-node traffic pattern. We use growth factor $f = 6$ in ψ as described in Section 4.4. Centrality based power control mechanism achieves significantly better load balancing compared to SPR in G_C and divergent routing schemes. Divergent routing schemes increase the average relay load of nodes when compared to SPR but decreases the overall deviation, which shows better load balancing. On the other hand, ψ decreases the standard deviation of relay load substantially without even increasing the average relay load. In most cases, ψ achieves upto 50% better load balancing than divergent routing schemes which is a useful practical result.

(a) Relay load of nodes in (i) shortest path routing (ii) centrality based power assignment ψ with $f = 6$; Y-axis shows relay load in number of packets

(b) Load balancing using ψ in grid ($n=400$); Y-axis shows relay load in number of packets

Figure 4.4: Load balancing effects of centrality based power assignment ψ in grid topology

(a) Load balancing, ψ random topologies ($n \approx 400$); Y-axis shows relay load in number of packets

(b) Load balancing, ψ clustered topologies ($n \approx 300$); Y-axis shows relay load in number of packets

Figure 4.5: Load balancing effects of centrality based power assignment ψ in random and clustered topology

(a) Relay load compared to divergent routing; Y-axis shows relay load in number of packets

(b) Path characteristics compared to divergent routing

Figure 4.6: Comparison of relay load and routing path characteristics of centrality power assignment and divergent routing

Figure 4.7: Load balancing with ψ in uniform node-to-gateway traffic ($n = 400$); Y-axis shows relay load in number of packets

Fig. 4.6b shows comparison of average routing path stretch and distance stretch between the same set of schemes. Average routing path stretch can be defined as average ratio of hop-length of routing paths in any load balancing scheme to hop-length of the shortest routing path. Average distance stretch can be defined as average ratio of Euclidean length of a routing path (summation of length of all of its hops) to actual Euclidean distance between source and destination. This measures on an average how much routing paths of a scheme deviates from the straight line between the endpoints. All the divergent routing schemes increase path and distance stretch compared to SPR in Compow graph. Different from this, ψ actually reduces path stretch below one. This is because power control increases network connectivity which reduces number of hops required to be taken to reach the destination. Also, ψ reduces distance stretch when compared to Compow graph because increased connectivity makes end-to-end shortest paths deviate less from the straight line. It is generally believed that when divergent routing is used for load balancing, stretch factor and load balancing ratio are inversely proportional to each other [96]. As shown in [65], divergent routing strategy which has stretch factor of σ with compared to shortest path routing, can achieve load balancing ratio of $O(\sqrt{n/\sigma})$. But when power control is used for load balancing, it is in fact possible to reduce stretch factor together with load balancing ratio, using shortest paths only.

As we saw that the centrality based power control yields improved load balancing with node-to-node traffic, we now discuss how the scheme performs with nodes-to-gateway traffic pattern. Fig. 4.7 shows the relay load of nodes when nodes send traffic to a central sink. When $f = 1$, all packets have to pass via the first tier nodes (neighbors of the sink), and hence their relay load is the maximum in the network. As the growth factor increases, nodes in the subsequent tiers are assigned high transmission power which allows them to jump over the first tier nodes. The relay load gets quickly balanced among nodes (lower standard deviation), and the overall behavior is similar to that in the case of node-to-node traffic.

4.5.2 Throughput Capacity

Increasing power levels of nodes certainly results in better load balancing, but it also affects achievable spatial reuse and throughput. Increasing communication range and connectivity of nodes using power control results in longer links which causes interference in a larger area, reducing simultaneous transmissions. In this section, we show that centrality based power control also increases throughput capacity in random and clustered topologies under uniform node-to-node traffic. In case of uniform topologies such as a grid, centrality based power control shows a trade-off between load balancing and throughput capacity.

We use spatial reuse TDMA-based greedy link scheduler ([45], [118]) for generating time slotted, conflict-free and feasible link transmission schedule. The end-to-end traffic demand between nodes is represented using a traffic demand matrix (T_R). Once the shortest path routing is performed, T_R yields per-link transmission matrix (T_X). We assume that there is a central controller entity which performs link scheduling. In the operation of greedy scheduler, first all links of T_X are sorted based on their interference score. Interference score of a link is the number of other links with whom the given link interferes and hence can not be scheduled simultaneously. Then scheduler chooses the first link in order to be scheduled in the current slot and tries to add more and more non-interfering links greedily until no more links can be added to the slot. The procedure repeats until all transmission requests of T_X are satisfied. [45] showed that such a scheduler has the time complexity of $O(m \cdot n \cdot T)$, where $T = \sum_{i=0}^n \sum_{j=0}^n T_{X_{ij}}$. If the total offered load $G = \sum_{i=0}^n \sum_{j=0}^n T_{R_{ij}}$ and greedy scheduler requires S slots to schedule all the links, the network throughput is G/S traffic units per unit time. The TDMA scheme used here is centralized and we assume that there is tight synchronization between nodes, and resultant TDMA schedule is distributed to the nodes without any additional delay. Such an idealistic TDMA scheme is appropriate to study performance of centrality based power control in its most general form which is the central focus of the work.

We assume that simultaneous transmissions on two links uv and xy results in collision-free data reception at the receivers *iff* $d_{ux}, d_{uy}, d_{vx}, d_{vy} > (\Delta \cdot d_{uv})$ and $d_{ux}, d_{uy}, d_{vx}, d_{vy} > (\Delta \cdot d_{xy})$,

where d_{xy} is the distance between nodes x and y and interference ratio $\Delta = 2$. As an example, in coarse-grained TDMA, if every slot is 1 second and channel goodput (B) is approximately 6 Mbps (as in 802.11b without RTS/CTS) in absence of interference, then resultant throughput with above mentioned TDMA scheduler is $(G/S) * B$.

It is important to note that heterogeneous power assignment using centrality leads to asymmetric links. The existence of asymmetric links can cause retransmissions at both MAC and transport layers and can result in duplicated data. For MAC layer, there are two ways of dealing with the problem. First way is to ignore the MAC layer acknowledgements and simply rely on transport layer to guarantee a reliable delivery. The presented scheme of centrality based power assignment can use this solution for implementation. Second, if there are MAC layer acknowledgements, we assume that the receiver of the link uses sufficiently high transmission power just to transmit an ACK to the transmitter. This allows the receiver to acknowledge the data reception even though its assigned power level as per the centrality strategy is lower. The resultant network graph after centrality based power assignment is directional due to non-uniform nature of power assignment. Even though routing is performed on asymmetric links, when these links are scheduled, we assume that receiver is using high transmit power to acknowledge the transmitter. This is justified further by the interference model presented above which also considers interference caused by the receiver's acknowledgement to other links and assumes that receiver is using transmitter's power level only for the purpose of acknowledgement. In the context of transport layer, when transmissions follow a single- (or few-) hop path from a node X to a node Y, but a multi-hop path from Y to X, resulting in delayed or lost acknowledgements and potentially multiple transmissions, hence duplications at the transport layer. This consideration is also important and we believe methods provided in [37, 152, 60] can be used to address it.

Uniform Node-to-node Traffic

First, we consider uniform node-to-node traffic pattern. Fig. 4.8a shows the aggregate network throughput for three different topologies. We choose a large number of distinct network flows ($\approx \frac{n(n-1)}{2}$) where each flow carries amount of traffic which is uniform across all flows. It is important to note that we have examined the effects of different power level on the throughput under the same conditions of network load, but the results regarding their relative performance are not dependent on any particular network load; thus results presented below hold for higher network loads as well – or any network load that is within the network capacity region. In case of grid, increasing the growth factor results in initial decrease of capacity followed by an increase. Even though load balancing improves with increase in growth factor, highest capacity is achieved at $f = 1$ in case of grid topology. This is because highest spatial reuse is achieved at $f = 1$ in case of grid and spatial reuse gradually decreases after that. On contrary, in case of random and

(a) Throughput capacity with centrality power control with node-to-node traffic ($n = 400$)

(b) Throughput capacity with centrality power control with node-to-gateway traffic ($n = 400$)

Figure 4.8: Analysis of throughput capacity of Centrality-based power control

clustered topologies, increasing growth factor also increases the throughput capacity along with better load balancing. As expected, random and clustered topologies achieve lower throughput compared to grid case. In random topologies, increasing power levels of certain nodes decreases the spatial reuse, but it also increases the connectivity among nodes. This results in many of the source nodes directly reaching the destination nodes and average routing path length decreases. The positive effect of reduced number of transmissions dominates the negative effect of reduced spatial reuse. This is especially a notable result because the reduction in relay load due to increased range more than offsets the reduction in spatial reuse due to increased interference, and hence overall throughput capacity improves.

In clustered topologies, inter-cluster links become traffic bottlenecks and they are required to be scheduled large number of times. This results in decreased throughput. Now, as the growth factor increases, more and more inter-cluster links are established which share the burden of previously bottleneck links and also improve the opportunity of spatial reuse. Due to better load balancing and improved spatial reuse, increasing growth factor in clustered topologies also increase the throughput. Since most of the real world topologies are either random or clustered, centrality based power control can yield good benefits of load balancing and capacity in them. Also, decision of choosing appropriate value of f depends on the network topology along with many other factors such as traffic pattern, traffic load, wireless radio characteristics such as maximum transmission power etc.

Uniform Node-to-sink Traffic

We now consider uniform node-to-sink traffic pattern. Fig. 4.8b shows the aggregate network throughput for three different topologies. In this traffic pattern, all nodes send data to the sink, and the amount of traffic in flows is uniformly distributed. As we can see that increase in the growth factor results in increased throughput in all three topologies.

As expected, the nodes around the sink have to perform the highest amount of relaying since all routing paths have to go through one of them. The links around the sink have to be scheduled a large number of times but they can not be scheduled in the same time slot since they mutually interfere. The resultant hot-spot reduces the network throughput due to disproportionate load balancing. When centrality based scheme is applied, nodes that were previously 2 hop or 3 hop neighbors of the sink (or even beyond that) can now directly reach the sink. This indeed decreases the spatial reuse due to creation and scheduling of long links, but the total number of required transmissions also decrease. Again, as it was in the case of node-to-node traffic, the decrease in required number of transmissions to be scheduled is faster than the decrease of spatial reuse which yields a net advantage in network throughput. The effect continues with increase of the growth factor until a point beyond which increasing the

Table 4.1: MicaZ specifications [5, 102]: transmission power levels, consumption and range

Transmission power level	Power consumption (mA)	Communication range (meters)
1	8.5	10
2	9.9	15
3	11.2	25
4	12.5	35
5	13.9	45
6	15.2	50
7	16.5	55
8	17.4	65

growth factor does not have any impact on network throughput.

A rather similar behavior is observed in the case of poisson-random topology. In the case of clustered topology, the increase of throughput is observed to be sharper in comparison with grid and random cases. This is attributed to the fact that for a given average inter-cluster distance, at a certain value of f , the inter-cluster connectivity sharply increases which in turn also increases the spatial reuse (as it was in the case of node-to-node traffic) due to load sharing among inter-cluster links.

4.5.3 Energy Efficiency and Network Lifetime

In this section, we present the numerical results for energy efficiency of load balancing mechanisms and resultant network longevity. We model our sensor network where each sensor is a widely used MicaZ [14] node. Specifically, they utilize CC2420 [5] radio chip which offers as many as eight different transmission power levels. As described in [154], these Tx power levels have energy consumption in the form of $P_T(d) = P_{T0} + P_A(d)$ where $P_T(d)$ is the total power consumption to transmit at a distance d which contains a component P_{T0} independent of d and another component $P_A(d)$ dependent on d . The transmission range independent component P_{T0} also has a significant impact on overall consumption because no matter at what power level a transmission occurs, P_{T0} is always accounted for all transmissions in the network. The actual power consumption (in mA) at eight discrete power levels are described in Table 4.1. The typical reception power consumption is 12 mA. It is obvious that the presented scheme has a crucial dependence on actual signal propagation model and resultant communication range. As mentioned before, we do not assume a specific signal propagation model. Instead, for simulations, we rely on real-world measurements of MicaZ listed in [102] for the relationship

between transmission power and corresponding communication range (listed in Table 4.1) in standard outdoor environment. The maximum transmission range (d) achievable at various Tx power levels is determined in such a way that reception at distance d has above 95% packet reception rate [102]. It is assumed that power consumed in transmission and reception functions dominates the consumption of all other tasks and ideal MAC protocol is employed for low-level implementation. For simulations, continuous power levels resulting from centrality based power assignment are mapped to nearest higher discrete power level. Each node is powered by two AA batteries (2000 mAh, 3 V) and transmission of packets are assumed to be 500 ms long.

Fig.4.9a shows global energy expenditure with various load balancing schemes when every node in the network sends one packet to every other node in the network. As explained before, any divergent routing scheme consumes more energy than SPR in G_C because of increased path lengths. On the other hand, ψ reduces the total number of transmissions and receptions (path length) which results in reduced energy consumption. This is in line with results presented in [154] which shows that routing on shortest paths in a more connected network (fewer hops) is more energy efficient.

Uniform Node-to-node Traffic

We consider two measures of network lifetime in the case of uniform node-to-node traffic pattern: time to death of the first node and loss of coverage. These measures are discussed in [42] and are widely used in sensor network research. In both the measures, after certain number of messages are transferred between nodes, a node in the network ends up depleting its battery which is marked as the death of the first node. This first node is highly likely to be located near the center in the case of SPR in G_C and often has to perform maximum amount of relaying. Fig.4.9b shows comparison of death of first node based network lifetime in SPR in G_C , curve-ball routing and centrality based load balancing. Divergent routing schemes like curve-ball improves on time to the first death by better distributing the relay load in the network. The ψ improves the lifetime significantly because it achieves better load balancing than other mechanisms.

In the second measure of lifetime, it is assumed that every sensor has a role of sensing certain number of *event points*. Every point is assumed to be covered by approximately 15 sensors. This way, when co-located 15 sensors die, a particular event point becomes uncovered, resulting in dysfunctional state of the network. This is different from the first measure because network can still continue performing its work even after the death of first node. As can be observed in Fig.4.9b that ψ achieves significantly longer lifetime because of better load balancing and reduced path lengths. As before loss of coverage occurs near the center for SPR in G_C and near the area between periphery and center in curve-ball routing. It was observed that in the case of ψ , loss of coverage happens almost uniform randomly in the network, which demonstrates

(a) Global energy consumption

(b) Network lifetime in uniform node-to-node traffic (n=1000)

Figure 4.9: Network lifetime and global energy consumption of Centrality scheme and other divergent schemes

improved load balancing.

Uniform Node-to-sink Traffic

Now we consider the uniform node-to-sink traffic pattern which is a more practical case for real world sensor deployments. Since all nodes are sensing and transferring their packets to the sink, disconnection of the sink from the nodes is a useful and accurate network lifetime measure [101]. Specifically, it was shown that when all the nodes providing connectivity to the sink (first tier nodes) exhaust their battery levels, sink can no longer be reached and the network becomes dysfunctional. Here it is also assumed that sink itself is not power constrained. When the sink is placed at the center of the network, there is no significant benefit of divergent routing because all the packets have to eventually traverse through the first tier nodes only. Hence, only SPR is considered here for comparison. In a typical lifetime of such a network, all nodes start by sending packets to the sink and nodes in first few tiers start depleting their batteries very quickly. At a certain point, a node, most probably in the first tier, dies but other nodes of the first tier still provides sink connectivity. As an when more and more first tier nodes die, it increases the relay load of remaining first tier nodes since all shortest paths to sink now pass through them. Eventually, all nodes in the first tier deplete their batteries and suddenly entire network becomes disconnected. Note that we restrict our attention to single sink case here. In the case where there exists multiple sinks, and nodes can switch to a different sink depending on the connectivity is beyond the scope of this work. This is because such a switching changes the traffic pattern which in turn requires recalculation of centrality values and re-assignment of transmission power. Such a dynamic strategy and resultant protocol is part of our future work.

The case of single sink is displayed in Fig.4.10a where all nodes ($n=1000$) are assumed to be operating at Compow power level and have uniform battery levels too. Fig.4.10a depicts number of nodes that can not reach the gateway because either they have depleted their batteries or they are disconnected from the sink due to deaths of other nodes. Initially, most of such depicted nodes are the ones who have depleted their batteries and are mostly in first tier. Once all the nodes of first tier die, all remaining nodes suddenly become disconnected (vertical straight transition of the curve) and network lifetime has ended. It is worth noting that at this point nodes who are disconnected but yet not dead, have not even depleted half of their batteries in most cases.

To mitigate the problem, [101] presented an approach where nodes near the sink (first few tiers) are assigned higher battery levels than other in such a way that global battery budget remains unchanged. In the simplest case of their solution, there are two battery levels in the network where 13% of total nodes (near the sink) have 5718 mAh batteries while rest of 87% have batteries with capacity of 1442 mAh. Now, nodes who are responsible for relaying more

(a) Network lifetime in node-to-sink traffic

(b) Centrality based power and battery level allocation

Figure 4.10: Effects of centrality based power control on load balancing, energy efficiency and network lifetime

packets are assigned higher battery levels to live longer and increase network lifetime. We simulate this case and results are presented in Fig.4.10a which shows that even with just two battery levels, overall network lifetime can be about three times longer than the base case. The third case presented in the Fig. 4.10a is the case of load balancing with centrality based power control. Here, the battery levels of the nodes remain uniform but as before, nodes which are likely to relay more packets for others are assigned higher power levels. This way, as we move from the periphery towards the sink in the center, power levels of the nodes increase in every tier continuously. This allows the nodes away from the sink to jump over the first few tiers' nodes and directly reach the sink which reduces their relaying burden. Hence, relay load of nodes are better distributed among the nodes even in case of node-to-sink traffic pattern (not possible with divergent routing schemes). This results in deaths of nodes which are relatively more consistent over time (Fig. 4.10a) and significant increase of network lifetime is observed.

Betweenness centrality can also be used to assign battery levels to the nodes since the nodes which are likely to perform more relaying are actually the nodes which deplete their batteries before others. Fig. 4.10b shows the lifetime behavior of a network where nodes which are likely to relay more packets (in first few tiers) for others are assigned higher power levels as well as higher battery levels. The same algorithm presented in Section 4.4 is also used to perform battery assignment in a way that overall battery budget remains unchanged. Different from discrete multiple battery level case, here the battery levels of the nodes change continuously. As can be observed in Fig. 4.10b, such a power and battery assignment results in substantially longer network lifetime. The lifetime is even better than the case where only power levels are assigned using centrality but the battery levels are uniform. Though the death of the first node occurs earlier than other cases, an interesting observation is that node deaths and disconnections are more consistent over the time and uniform across the network which shows improved balance between relay load distribution and battery resource allocation.

4.6 Concluding Remarks

In this chapter, we proposed centrality based selective power control scheme which achieves better relay load balancing compared to divergent routing schemes. When centrality based power control is employed in the network, better load balancing can be achieved with shortest path routing. Various evaluations of network lifetime confirm that centrality based load balancing can increase network lifetime significantly in different traffic patterns. The presented scheme requires global knowledge for determining the centrality values and power levels.

Chapter 5

Availability and Performability of Urban-scale Mesh Networks

In the previous chapters, we studied two very important issues of wireless mesh networks - analysis of throughput capacity and relay load balancing - using transmission power control. We will investigate network utilization and fairness issues in Chapter 6 using the back-pressure utility maximization framework. As we had mentioned before, one of the key advantages of deploying a wireless mesh network for the purpose of Internet access is its salient characteristic of robustness. A mesh topology inherently provides tolerance to component failures (link failures, node failures etc.) by facilitating redundant routing paths between nodes. In this chapter, we provide an in-depth study of this robustness characteristics using various service continuity metrics.

As opposed to the time of its inception, current wireless mesh network deployments are expected to deliver carrier-grade services to its users. With this increasing expectations, it is generally being recognized that there is a lack of good understanding of level of service continuity that mesh networks can provide to its users. In this work, we study two essential service continuity metrics – connection robustness (availability) and performance robustness (performability). Availability is the fraction of time a mesh network is available to its users, while performability is a composite measure of performance (here – throughput) and robustness that captures aggregate experience of the mesh users over a long period of time.

At a high level, contributions of the work are as follows - First, we define both service continuity metrics, and develop efficient algorithms for estimating them. Second, we apply these methods to determine availability and performability of two existing urban mesh networks (GoogleWiFi [9] and PoncaCityMesh [20]), and show that both the networks can not guarantee a reasonable level of connection or performance robustness. Third, we embark on a comprehensive study to understand the relationship between fundamental deployment factors and the

robustness metrics. Our study reveals numerous novel insights that can help in designing mesh networks with high availability and performability.

In the next Section, we provide a brief primer of service continuity metrics that are most relevant in case of mesh networks. In Section 5.2, we describe the service continuity issues in further details and motivate the problem.

5.1 Principles of Network Service Continuity

The general concept of service continuity can be quantified in various different metrics, reflecting different needs, concerns and perceived risks. We start with a short primer on the general concept of service continuity, and introduce two of these metrics. We argue that availability and performability are useful metrics to reflect the goal of service continuity for the emerging uses of the mesh paradigm.

The fundamental functionality of any networked system is to enable communication among the desired entities. This functionality is perceived by networks users as a service, and any disruption in the service (partial or complete) implies failure of the network as a system. In last four decades, disruption of networking service is studied in various forms such as reliability, dependability, fault-tolerance, survivability, trustworthiness, robustness etc. The term reliability was introduced in military in order to define service disruption of a stand-alone computing system due to hardware failures. Along the same line, fault-tolerance was introduced as a concept to capture the effects of software failures (mostly due to design issues). Later, as the systems became more and integrated, the dependability (often used as an umbrella term) concept evolved to encompass hardware and software failures and its effects. With the invention of Internet, the need of studying failures in a networked computing system became apparent which gave birth to another (rather general) term, survivability. In the last decade, failures due to malicious attacks and intentional disruptions have given rise to the concepts of security and trustworthiness. Other definitions of service expectations (e.g. QoS) have evolved in parallel but their meanings have remained more subjective.

Service continuity (also known as survivability) is the ability of a network system to continue providing service to its users in an event of a failure. It acts as characterization of the time-varying performance of the network in the immediate aftermath of a fault until a new steady state is achieved. The term survivability itself is not only a quantitative measure of the system's ability to continue functioning in case of failure, but it is used more generally as an encompassing quality that includes many related measures. Various metrics of service continuity are shown in Fig. 5.1. Relevant metrics of service continuity are discussed next.

Figure 5.1: Metrics of Service Continuity

5.1.1 Reliability

Different from its mundane meaning, reliability of a system is a mission oriented question.

Definition 1. *Reliability is the probability of a system performing its purpose adequately for the period of time intended under the operating conditions intended.*

In other words, if a system started in expected service level at time $t = 0$, and the time of the mission is T , then reliability is the probability that the system will not fail until the end of the mission. An example would be what is the probability that a car engine will work failure-free for the car race?

Formally, the reliability function can be defined as below -

$$R(t) = P\{\text{no failure in time}[0, t]\} \quad (5.1)$$

Note that $R(t)$ is always a non-decreasing function with $R(0) = 1$ and $R(\text{inf}) = 0$ (refer Figure 5.2). *Cumulative Failure Function* $Q(t) = 1 - R(t)$ is the probability that there is at least one failure in time interval $[0, t]$. In some systems as it is shown later, reliability is desirable to be defined as complimentary CDF (cumulative distribution function) of time between failures.

Figure 5.2: Reliability is a mission-oriented question

Let $f(t)$ be the failure density function that represents probability density function of time to next failure.

$$\int_{t_1}^{t_2} f(t)dt = \text{probability of at least one failure in time interval } [t_1, t_2] \quad (5.2)$$

By definition of Cumulative Failure Function,

$$Q(t) = \int_0^t f(t)dt; \quad (5.3)$$

and

$$R(t) = 1 - \int_0^t f(t)dt = \int_t^{\infty} f(t)dt \quad (5.4)$$

Wireless mesh networks are not ephemeral mission-oriented systems. These networks are expected to serve the purpose for relatively long time and are expected to be expanded several times during its lifetime. This makes reliability an unsuitable metric to study wireless mesh networks' service continuity.

5.1.2 Availability

The mission-oriented nature of reliability is suitable for analyzing systems which should provide uninterrupted service for predetermined duration. This is mainly because in such mission-critical systems, consideration of component repair and system restorability is unrealistic. The systems where expected service is almost perpetual in nature (such as in Internet), the repairs are frequent and it is necessary that they are accommodated in the analysis. The measure suitable for such analysis is that of system availability.

Definition 2. *Availability is the probability of finding the system in the operating state at any arbitrary time in the future.*

Note that unlike reliability, we now consider systems that can be repaired. As an example, a question such as “what is the probability that a connection to a web server is available when my computer is turned on?” is an availability question. Availability can be calculated using:

$$\text{Availability} = \frac{\text{Time for which the system was operational}}{\text{Total time of observation}} \quad (5.5)$$

Network Availability

Network availability is typically understood with consideration of its high-level components such as nodes and links. For illustration purposes (refer to Fig. 5.3), let us consider a network where edges are prone to failure with a given probability (component availability), while the nodes do not fail. Any such network can be modeled using a random graph. Let $G(V, E)$ be the network graph with n nodes and m edges. or the edge set $E = \{e_1, e_2, \dots, e_m\}$, let $P = \{p_{e_1}, p_{e_2}, \dots, p_{e_m}\}$ be the probabilities of their correct operation. Given these settings, many availability problems can be analyzed for such a network. Three availability problems listed below have been widely studied in literature:

Definition 3. *2-terminal Availability is the probability that given two nodes are connected with each other.*

Definition 4. *Network Availability (or connectivity) the probability of all nodes being connected with each other.*

Definition 5. *k-terminal Availability is the probability that given k nodes are connected.*

All the three availability problems are known to be computationally expensive even for a small network size. This can be understood from the illustrative network of Fig. 5.3. Finding the probability that node A and node F are connected requires calculating a large polynomial of p .

Figure 5.3: Graph representation of a network where each link can operate correctly with probability of 0.9

To understand this, first let us assume for now that all the edges in the network operate with the same probability p . A *pathset* in context of any availability problem is a set of edges, when operational, guarantees connectivity between the desired set of nodes (2 nodes, all nodes or k nodes). Similarly, a *cutset* is a set of edges when failed causes disconnection among desired set of nodes. Let N_i denote the number of pathsets with i edges. The reliability now can be written as a polynomial in p :

$$Availability(G) = \sum_{i=0}^m N_i p^i (1-p)^{m-i} \quad (5.6)$$

The above availability polynomial is written in terms of pathsets, and similar polynomials can be written in terms of cutsets and complements of pathsets. Finding sequence of coefficients $\{N_1, N_2, \dots, N_m\}$ (or $\{C_1, C_2, \dots, C_m\}$ for cutsets) is actually a problem of counting pathsets which in turn makes the availability evaluation problem a counting problem.

In case of 2-terminal availability, pathsets are all possible paths which connects the two nodes and cutsets are all possible edge-cuts which disconnects them. Similarly, in network availability, pathsets are all possible spanning trees and cutsets are all possible network cuts. Now, let l be the size of minimum cardinality minpath (minimal pathset) and similarly let c be the size of minimum cardinality mincut (minimal cutset). It was shown in [52] that if, for an availability problem, it is NP-hard to compute either l or c , the corresponding availability problem is also NP-hard. Similarly, if computing N_l or C_c (or any other coefficient) is #P-complete, the computing corresponding availability is also #P-complete. 2-terminal availability, all-terminal availability and k -terminal availability, all are proven to be #P-complete using these facts since computation of all coefficients are #P-complete in almost all cases.

Table 5.1: Complexity of availability problems [52]

Problem	Graph	MinPath	MinCut
2-terminal	#P-complete	open	polynomial
network	#P-complete	polynomial	open
k -terminal	#P-complete	open	open

For a network such as the one shown in Fig. 5.3 where edges can be in either operational or failure mode, the complexity of availability problem can be understood as follows. In a network with m edges where edges are either in failed or operational mode (and nodes do not fail), there are a total of 2^m network states. Depending on the desired set of nodes between which the connectivity is necessary, 2-terminal, network or k -terminal availability can be understood in terms of network states. Let C be the set of states where desired set of nodes are connected, and similarly, let D be the set of states where desired set of nodes are disconnected. In such a case, availability is defined as $\frac{|C|}{2^m}$, and similarly, unavailability can be defined as $\frac{|D|}{2^m}$.

It is clear that availability is an important metric to be studied in systems such as wireless mesh networks where repairs are feasible and natural. In many cases as we will see later, links of a wireless mesh network are available or unavailable which makes studying mesh availability especially useful.

5.1.3 Performability

Availability is one of the many fundamental properties of any network, and it is widely studied in literature. Though this is true, there are certain limitations of the availability metric. Availability can only distinguish between connected states and disconnected states of the network. Due to this characteristic, it can not be applied to a performance degradable system. As an example, failure of a link might not cause a complete disconnection of the network but might affect the expected performance delivered by the network (such as throughput, delay etc.). The binary nature of availability is not sufficient to model such performance varying states of the network. Many of the systems (especially networked systems) being performance degradable in nature, *performability* metric has been defined and studied in literature [76].

Formally, let $S = \{s_{e_1}, s_{e_2}, \dots, s_{e_m}\}$ describe a network state where $s_{e_i} = 1$ if edge e_i is operational and 0 otherwise. Let $\mathcal{X}$ be the set of all 2^m network states. Also, let $F(S)$ be a performance function defined on the state S . The probability that the system is in state S is given by $\Pr(S)$ (also referred as state occurrence probability). The well-known performability metric can be calculated as

$$\bar{P} = \sum_{S \in \mathcal{X}} (F(S) \cdot \Pr(S)) \quad (5.7)$$

It is worth noting that availability can be regarded as a special case of more general metric performability. This happens when the performance function is defined as a binary connectivity function, meaning when the desired set of nodes are connected $F(S) = 1$, and 0 otherwise. Also, performability permits statistical dependence among link failures (as opposed to availability).

The computation complexity of performability in turn involves complexities of availability and performance problems. Depending on the networked system at hand, its performance can be a feasible (e.g. wired networks with known traffic demands) or a hard problem (e.g. wireless networks). Note that in cases like availability problem, $F(S)$ can be binary (S is connected or not) but $F(S)$ can take any form in general which makes the performability evaluation problem even more challenging. Its exact evaluation is known to be a hard problem [75] and most of the current evaluation schemes depend on state generation methods.

Similar to availability, we will study performability of mesh networks since they are by nature performance degradable systems. It is especially interesting for a network designer to understand how much performance can be guaranteed to mesh users in case of failures.

5.2 Problem Description - Service Continuity of Mesh Networks

Current WMNs are expected to deliver carrier-grade services to its users. With these increasing expectations, it is generally being recognized that fundamental principles of service continuity are not well understood for WMNs. This is natural since ad-hoc networks (from which the mesh concept was derived) were never designed to provide carrier-grade services. WMNs, on the other hand, must be analyzed in the same context as other contenders such as cellular networks. For example, there already exists various methods for evaluating service continuity for cellular networks (e.g. [34],[143]) in case of component failures.

In this work, we present a study of evaluation and analysis of service continuity of urban-scale WMNs. We consider two basic service continuity metrics - connection robustness (modeled as availability) and performance robustness (modeled as performability):

(1) K-center Availability (KCA): The availability metric measures what fraction of time a given system is in working state. We name the availability of WMNs to be k-center availability as the Internet gateways of WMNs are ideally the centers of mesh network connectivity graph. The KCA problem finds the probability that every mesh node is connected to at least one of the k Internet gateways.

KCA is an essential service continuity metric since it models if WMN as a system is available

to its user or not. Current mesh network users expect an “always-on” attribute in service where total disruption is seen as a serious failure of the network. Maximizing the fraction of the time a mesh can provide Internet access to its users should be considered as an imperative design objective.

(2) K-center Performability (KCP): The performability metric is a joint measure of system performance and its availability. A WMN that enables continuous Internet connection of its users but does so with frequent lapses in performance (such as throughput, delay etc.) can not provide a satisfactory user experience.

The KCP metric accounts for what is the performance of a given WMN and how reliably the performance is delivered to its users. Increasing the KCP of WMNs ensures that users encounter fewer and fewer variations in the performance they expect from WMN.

The contributions of the work are as follows:

First, we formally define KCA and KCP. It is shown that their exact evaluation for even a moderate size network incurs prohibitive computational complexity. We develop efficient algorithms that can estimate the quantities with reasonable accuracy even for a large urban-scale WMN (as many as 500 nodes). For KCA, we have developed a constrained Monte Carlo state generation method that utilizes bounds derived from the network graph to increase efficiency of Monte Carlo simulation. In the case KCP, we apply the most probable states generation method to a subset of components that are crucial in determining network performance.

Second, we apply these methods of evaluating KCA and KCP to two existing urban mesh networks (GoogleWiFi [9] and PoncaCityMesh [20]). We show that their current design can not provide a reasonable level of service continuity.

Third, in order to further understand the impact of deployment factors on KCA and KCP, we embark on a comprehensive study of their relationship using hundreds of hours of simulations. Using the results, we identify some crucial design principles that can help in designing WMNs with high KCA and KCP. An important contribution of this work is that some of these principles are different (often contradicting) than conventional understanding. As an example, we will show that in fact higher transmission power can be beneficial although traditionally it is considered harmful due to interference.

5.3 Link failures in wireless mesh networks

Compared to ad-hoc networks, nodes are less vulnerable to failures in a mesh network. This is mainly because the nodes in carrier-grade mesh networks are typically not power constrained (e.g. battery operated) or resource constrained. On the other hand, links are inherently susceptible to failures due to unpredictability of wireless medium. In urban environments especially, radio propagation can be highly non-uniform and coverage regions of mesh nodes can be of

nearly arbitrary shapes. This non-uniformity in radio propagation which results in probabilistic connectivity between mesh nodes is known as *shadowing*. Due to shadowing, the signal power at different points with same expected path loss shows significant variations. Prior measurement studies have shown that path loss at a particular location is random and distributed log-normally around the average distance dependent path loss. This makes the received signal strength inherently probabilistic. Formally, as shown in [130], for a transmitting node u , the received signal strength at receiver v at a distance d_{uv} is modeled as :

$$PR_{dBm}^v(d_{uv}) = PT_{dBm}^u - PL_{dB}(d_0) - 10 \eta \log_{10} \left(\frac{d_{uv}}{d_0} \right) + S_{dB}^\sigma$$

where PT_{dBm}^u is the transmit power, $PL_{dB}(d_0)$ is the reference path loss at a distance d_0 , η is the path loss exponent and S^σ is a zero-mean Gaussian variable with standard deviation σ . A wireless link exists between u and v if the received power $PR_{dBm}^v(d_{uv})$ is not less than some given minimum threshold P_{min} . Such a threshold is typically referred as the *receiver sensitivity*. The distance d_r is the communication range in the absence of shadowing (i.e. $\sigma = 0$)

$$d_r = d_0 10^{\frac{PT_{dBm}^u - PL_{dB}(d_0) - P_{min}}{10 \eta}}$$

Error function (or Q-function) can be used to determine the probability that the received signal power larger than P_{min} . The probability ($\Pr(uv)$) that there exists a wireless link between u and v can be given by –

$$\Pr \{PR(d_{uv}) \geq P_{min}\} = \frac{1}{2} \left[1 - \operatorname{erf} \left(\frac{10}{\sqrt{2}} \cdot \log_{10} \frac{d_{uv}}{d_r} \cdot \frac{\eta}{\sigma} \right) \right] \quad (5.8)$$

Typically state-of-the-art measurement and modeling methods [135] are used to derive the exact values of η and σ for a given outdoor environment. The value of d_{min} (along with receiver SINR) determines the data rate at which the established link will operate. Given the RF profile (η , σ and $PL_{dB}(d_0)$) of the environment, the mesh node profile (receiver sensitivity and corresponding data rates) and node positions, Eq. 5.8 can be used to determine *shadowing probabilities* of existence of links (or its complement, failure of links). Fig. 5.4 shows what is the impact of varying power levels on shadowing probabilities. As expected, when the transmit power level of nodes increase, the distance upto which there is a non-zero probability of having a link also increases.

Formally, let $G_P(V, E, P)$ be a the network graph of a mesh network. let n be the number of mesh nodes and m be the number of edges. For the edge set $E = \{e_1, e_2, \dots, e_m\}$, let $P = \{p_{e_1}, p_{e_2}, \dots, p_{e_m}\}$ be the probabilities of their correct operation. We refer to G_P as a probabilistic connectivity graph. The failure probabilities can be determined by any method

Figure 5.4: Impact of transmit power on shadowing probabilities, $\eta = 3.5$, $\sigma = 8$ dB, $d_0 = 10$ m, $PL_{dB}(d_0) = 50$ dB.

which can model link failures of the given network. To focus on urban mesh networks, we restrict our attention to shadowing probabilities here. The probabilistic connectivity graph decouples the KCA and KCP evaluation methods (presented below) from how the link failure probabilities are determined. The evaluation methods can be applied to any set of edge failure probabilities given that the link failures are independent.

5.4 Algorithm for Evaluating KCA

In this section, we define KCA and provide the details of constrained Monte Carlo simulation method for estimating its exact value.

First, for G_P , let $K \subset V$ be a set of k gateways where $K = \{g_1, g_2, \dots, g_k\}$.

Definition 6. *K-center Availability (KCA) is the probability that $\forall u \in V - K$ is connected to at least one gateway $g \in K$.*

When all non-gateway mesh nodes can reach at least one gateway, we mark the network to

Figure 5.5: k-center availability is different than network connectivity

be *k-center connected*.

Different from various other approaches in literature which focus on deriving asymptotic results [40, 157, 77] for network connectivity, *we are interested in numerical evaluation of KCA*. Also, network availability can not be used for estimating KCA in any way because there can be a large number of network states where network is disconnected due to a link failure but the state is still k-center connected. This is shown in Fig. 5.5.

Other availability metrics are widely studied in network availability literature [52] but they are not useful in finding KCA. The most general form of availability problem is that of finding t-terminal availability which is the probability that the given t nodes are connected. The problem is known to be #P-complete [52] when $t = 2$ (2-terminal availability) and $t = n$ (network availability). Due to this, most of the current methods of finding 2-terminal and network availability rely on Monte Carlo state generation.

A mesh network with m links where each link is either available or unavailable has a total of 2^m possible network states. Since the focus of this study is to find availability of a large urban-scale mesh network, exact evaluation methods [52] such as complete state enumeration, graph transformation, factoring etc. are not useful. Such computational complexity has given rise to two approaches of calculating the availability.

Figure 5.6: Monte Carlo state generation is a process of generating states by picking up states uniform randomly out of the entire state space

First, a set of reasonable upper and lower bounds are derived based on the graph structure and link availabilities. In most cases, the bounds are computationally inexpensive to derive but their quality depends on various factors, and they are often too loose to be useful.

Second, Monte Carlo simulations are used to estimate the value of availability. In this method, a pre-calculated number of network states are uniformly chosen from all possible states. The actual availability value is then an estimate based on availability measure of these states. This can be further understood using Fig. 5.6 where a few states are uniform randomly chosen without any prior knowledge about the states. Each of the states is then evaluated to see if the state is available or not. The advantage of Monte Carlo method is that it allows faster unbiased generation of states which leads to better estimation of availability. On the other hand, the a large number of states are necessary to be generated in order to achieve a reasonable accuracy in estimate.

5.4.1 Constrained Monte Carlo Simulation (CMCS)

Fishman first proposed an availability evaluation scheme [61] (for 2-terminal availability) that combined benefits of both these approaches. He suggested that even if the bounds found are only reasonably good, they can be used to direct a Monte Carlo simulation to reduce the number of necessary samples. This means that bounds should be used to eliminate large number of states from the entire state space, and Monte Carlo simulation is then necessary to be ran only in remaining number of states. This is shown in Fig.5.7. With the bounds, we already know that all the states above the upper bound are connected and all the states below the lower bound are disconnected. Now, if we only generate the states in between the bounds (undetermined states) in our Monte Carlo simulation, fewer states will be necessary as compared to a naive Monte Carlo simulation. We refer to this scheme as a *Constrained Monte Carlo Simulation (CMCS)*.

It should be noted that there are multiple challenges in adapting CMCS scheme for mesh networks. First challenge is to derive a *reasonable* set of bounds which can be used in CMCS. This means that bounds derived in terms of k-center connected and disconnected states should

Figure 5.7: State space and availability bounds

be tight enough to be useful otherwise the CMCS method degenerates to a naive Monte Carlo scheme. Also, since we want to study KCA while varying topological factors like node density and transmission power level, the bounds should remain reasonable in all cases. Second challenge is that the CMCS method which was initially proposed for 2-terminal availability should be adapted for KCA. This requires that the characteristics of conditional state generation (explained below) should be maintained even when states are being generated for KCA evaluation. Next, we describe how bounds can be derived and present the CMCS method for KCA evaluation.

5.4.2 KCA Evaluation using CMCS

Let $S = \{s_{e_1}, s_{e_2}, \dots, s_{e_m}\}$ describe a network state where $s_{e_i} = 1$ if edge e_i is operational (available) and 0 otherwise. The state space with total of 2^m states is divided into two disjoint and exhaustive subsets $\mathcal{C}$ and $\mathcal{D}$. As shown in Fig.5.7, $\mathcal{C}$ is a set of all operational (k-center connected) states while $\mathcal{D}$ is a set of all failed (k-center disconnected) sets. We use edge-packing bounds which are described next.

Edge-packing bounds

In a graph $G = (V, E)$, an *edge packing* [52] of G by k graphs $G_1, G_2, \dots, G_K$ is obtained by partitioning the edge set E into $k + 1$ classes $E_1, E_2, \dots, E_k, U$ and defining $G_i = (V, E_i)$. This way, an edge-packing of a graph is a collection of edge-disjoint subgraphs of the graph. An edge-packing lower bound on the availability can be obtained by finding a set of *edge-disjoint*

minimal paths (edge-packing of minpaths), and obtaining the probability that all the edges of at least one of these paths operate correctly. Similarly, an upper bound on the availability can be obtained by finding a set of *edge-disjoint minimal cuts* (edge-packing of cuts) and finding the probability that all the edges of at least one of these cuts fail. The edge-disjointness ensures that failure of every path (or occurrence of any cut) is independent from others since failure of an edge will only impact one path (or cut) at most.

Lower Bound: For KCA, edge-packing of minimal pathsets is a set of edge-disjoint forests where in each forest, every tree contains a gateway and all mesh nodes belong to a tree. Let I be the total number of such forests which are denoted by $F_1, F_2, \dots, F_I$. Each forest is a union of a minimal path from every mesh node to a gateway. If all edges of at least one of these forests are operational, every mesh node can reach at least one gateway and the resultant state is operational. Let Ω_1 be the set of states where there exists at least one operational forest. By definition, Ω_1 is a subset of $\mathcal{C}$ as shown in Fig.5.7. Hence, a lower bound (B) on k-center availability is the probability that all the edges of at least one of these forests operate correctly

–

$$B = 1 - \prod_{1 \leq j \leq I} \left(1 - \prod_{e_i \in F_j} p_i \right) \quad (5.9)$$

Finding I edge disjoint forests where trees in each forest are rooted at gateways turns out to be a non-trivial task. This is because as per the Equ.5.9, more of such edge disjoint forests (maximize I) yields a better bound. Also, the lower bound improves if each forest contains edges which are more reliable (higher operational probability) compared to other non-forest edges.

To find this edge packing of forests, we first determine weight of every edge using $w_{e_i} = -\ln(p_{e_i})$. Now, let $d(u, v)$ be the total weight of all edges on the shortest path between u and v . We then partition G_P in subgraphs $G_{g_1}, G_{g_2}, \dots, G_{g_k}$ where $v \in G_{g_i}$ if $d(v, g_i) = \min\{d(v, g_i), g_i \in K\}$, and $e_i \in G_{g_i}$ if and only if both endpoints of e_i belong to the same subgraph. Let $\kappa(G_{g_i})$ be the edge connectivity of G_{g_i} and let $\kappa(G_P) = \min\{\kappa(G_{g_i}), g_i \in K\}$. Now from Tutte's theorem [151], $I = \lfloor \kappa(G_P)/2 \rfloor$ and G_P contains at least I edge disjoint forests where each forest contains a tree belonging every subgraph G_{g_i} . Once we have determined I , we can find these edge disjoint forests using method proposed in [136]. To find I forests in which every node can reach a gateway using fewer and more reliable edges, we first find cw_{e_i} score of every edge in a G_{g_i} . That is, $\forall e_i \in G_{g_i}$ between u and v , let $cw_{e_i} = \min\{d(u, g_i), d(v, g_i)\} + w_{e_i}$. Now, we sort all $e_i \in G_{g_i}$ in increasing order of their cw_{e_i} scores, and input the sorted list to matroid partition algorithm of [136] which then finds I edge disjoint trees in each G_{g_i} forming I edge disjoint forests.

An example of edge disjoint forests is shown in Fig. 5.8. The network consists of four

(a) Edge disjoint forest - 1

(b) Edge disjoint forest - 2

Figure 5.8: A mesh network topology is (edge-)partitioned into two edge disjoint forests. As long as one such forest is operational (all its edges do not fail), the network is k -center connected.

Figure 5.9: Edges adjacent to every node in an independent set of a graph forms a minimal cut and all such cuts are edge disjoint. Occurrence of a cut leaves the network in a k-center disconnected state.

gateways where the trees of each forests are rooted. As long as one of the forest is operational, the network is k-center connected.

Upper Bound: There can be many different ways of determining a set of minimal cuts which can cause a failed network state. We observe that all adjacent edges of every node in an independent set of the graph forms a minimal cut, and all such cuts are also edge-disjoint. Since any such cut disconnects a node from rest of the network, such a node can not be connected with any of the gateway which is a failed state as per the definition. Let J be the total number of such cuts which are denoted by $C_1, C_2, \dots, C_J$. If all the edges of at least one of these cuts are failed, the resultant network state is failed. Let $\Omega_3 \subset \mathcal{D}$ be the set of states where there exists at least one failed cut. The upper bound (A) on k-center availability is the probability that all edges of at least one of these cuts have failed –

$$A = \prod_{1 \leq j \leq J} \left(1 - \prod_{e_i \in C_j} (1 - p_i) \right) \quad (5.10)$$

We use well-known greedy algorithm for finding a maximal independent set, and then obtain the cuts as above. An example of how independent set can be used to calculate upper bound is shown in Fig. 5.9.

Sampling Algorithm: As in Fig.5.7, since we already know that all states in Ω_1 are connected and all states in Ω_3 are disconnected, only the states in between the upper bound and lower bound are undetermined, and Monte Carlo simulations are required to determine their status. Let Ω_2 be the set of all such states. Note that Ω_2 is the set of states such that every cut C_j where $1 \leq j \leq J$ is operational and every forest F_i where $1 \leq i \leq I$ has failed. Since all cuts C_j are operational, there can be an operational path from every mesh node to a gateway but union of all such paths is not a forest among F_i .

The sampling algorithm is presented in Algorithm 1 which is adapted from [61, 104] for KCA. States of Ω_2 can not be uniformly sampled as in the naive approach because status of edges in a cut of a forest is conditionally dependent on each other. As described in [104], when sampling a state in Ω_2 , the edges which belong to a forest and/or a cut have to be sampled sequentially (Procedure sampleState, Part 1). If an edge belongs to a forest, its status depends on the constraint that requires at least one edge of the forest to fail. This ensures that the forest is not operational. Similarly, if an edge belongs to a cut, its status depends on the constraint that requires at least one edge of the cut to be operational. This ensures that the cut has not failed. The edges not belonging to a forest or a cut can be sampled independently (Procedure sampleState, Part 2). The number of states required to be sampled from Ω_2 depends on the level of accuracy needed in KCA estimate. We use the standard deviation of KCA estimate as a guideline. Since the standard deviation decreases as more and more samples are generated, its value can be calculated after every fixed number of samples. If the targeted accuracy is achieved, no more samples are necessary and procedure can be terminated with confidence.

Algorithm 1 Constrained Monte Carlo Procedure for KCA Estimation

INPUT:

Graph $G_P(V, E, P)$, $n = |V|, m = |E|$,
Set $K \subset V$ of k gateways, $K = \{g_1, g_2, \dots, g_k\}$,
 $P = \{p_{e_i}, \forall e_i \in E\}$ probabilities of correct operation;

Edge set of I forests $F_1, F_2, \dots, F_I$ and
Lower bound $B = 1 - \prod_{1 \leq j \leq I} (1 - \prod_{e_i \in F_j} p_{e_i})$,
 $H_1 = \bigcup_{j=1}^I F_j$;

Edge set of J cuts $C_1, C_2, \dots, C_J$ and
Upper bound $A = \prod_{1 \leq j \leq J} (1 - \prod_{e_i \in C_j} (1 - p_{e_i}))$,
 $H_2 = \bigcup_{j=1}^J C_j$, $H = H_1 \cup H_2$;

For $1 \leq i \leq m$ and $1 \leq k \leq I$,
 $Forest[e_i] = k$ if $e_i \in F_k$ and 0 otherwise,
 $\lambda[0] = 0$ and $\lambda[k] = \prod_{e_i \in F_k} p_{e_i}$;

For $1 \leq i \leq m$ and $1 \leq k \leq J$,
 $Cut[e_i] = k$ if $e_i \in C_k$ and 0 otherwise,
 $\omega[0] = 0$ and $\omega[k] = \prod_{e_i \in C_k} (1 - p_{e_i})$;

Accuracy threshold α ;

OUTPUT:

k-center availability (KCA)

METHOD:

$S = 0$;
while $stddev(KCA) \leq \alpha$ **do**
 $X = X + 1$;
 Generate a sample state using SAMPLESTATE;
 Check if the sample state is k-center connected;
 if The state is k – center connected **then**
 $S = S + 1$;
 $stddev(kcr) = \sqrt{\frac{(A-B)^2(1-S/X)(S/X)}{(X-1)}}$;
 end if
end while
Compute the k-center availability as follows:
 $KCA = B + (A - B) \frac{S}{X}$;
Return KCA

Algorithm 1 (Conti.) SampleState Procedure

▷ Sample edges in H - Part 1

```
while  $\lambda[k] \neq 0$  for  $1 \leq k \leq I$  and  $\omega[j] \neq 0$  for  $1 \leq j \leq J$  do
  Select an edge  $e_i$  from a  $F_k$  or a  $C_j$  with fewest remaining edges and  $\lambda[k] \neq 0, \omega[j] \neq 0$ ;
   $a = Forest[e_i], b = Cut[e_i]$ ;
   $p_{e_i}^* = \frac{p_{e_i} - \lambda[a]}{1 - \omega[b] - \lambda[a]}$ ;
  Sample  $u$  from uniform distribution  $U[0, 1]$ ;
   $s_{e_i} = \lfloor u + p_{e_i}^* \rfloor$ ;
  Set  $\lambda[a] = \frac{s_{e_i} \cdot \lambda[a]}{p_{e_i}}, \omega[b] = \frac{(1 - s_{e_i}) \cdot \omega[b]}{1 - p_{e_i}}$ ;
end while
```

▷ Sample edges in $E - H$ - Part 2

```
for all  $e_i \in E - H$  do
  Sample  $u$  from  $U[0, 1]$  ;
   $s_{e_i} = \lfloor u + p_{e_i}^* \rfloor$ ;
end for
Return the generated network state  $(s_{e_1}, s_{e_2}, \dots, s_{e_m})$ 
```

5.5 Algorithm for Evaluating KCP

We now discuss why KCP evaluation is necessary for WMNs, and describe an efficient method for estimating KCP of large urban-scale mesh networks.

5.5.1 Why KCP?

K-center availability can be used by a network designer to understand what is the likelihood that the network will remain k-center connected in case of link failures. For any given state of the network, availability yields a zero-one evaluation of whether all the mesh nodes are connected to a gateway or not. Though this evaluation is absolutely crucial in providing highly available service to the users, it gives little or no information about the actual user experience.

As an example, even in a k-center disconnected state, a few users might be able to successfully connect to Internet. On the other hand, a k-center connected state ensures connectivity of mesh users to Internet but does not guarantee any specific performance. This requires treating mesh networks as performance degradable system instead of denoting it to be operational or failed. This will also allow us to quantify the difference between links with different availability and data rates. As an example, we need a metric that can differentiate links with high availability but low data rate from links with low availability and high data rate.

Performability metric is typically used for such a purpose in system survivability studies. It analyzes the performance of a failure-prone degradable network and evaluates how reliably the performance will be delivered by the network. As in KCA, let $S = \{s_{e_1}, s_{e_2}, \dots, s_{e_m}\}$ describe a network state where $s_{e_i} = 1$ if edge e_i is operational and 0 otherwise. Let $\mathcal{X}$ be the set of all 2^m network states. Also, let $F(S)$ be a performance function defined on the state S . The probability that the system is in state S is given by $\Pr(S)$ (also referred as state occurrence probability). The well-known performability metric can be calculated as

$$\bar{P} = \sum_{S \in \mathcal{X}} (F(S) \cdot \Pr(S)) \quad (5.11)$$

Note that in cases like KCA problem, $F(S)$ can be binary (S is k -center connected or not) but $F(S)$ can take any form in general which makes the performability evaluation problem even more challenging. Its exact evaluation is known to be a hard problem [75] and most of the current evaluation schemes depend on state generation methods.

5.5.2 KCP for WMNs

For calculating performability of mesh networks, an obvious choice of $F(\cdot)$ is its aggregate network throughput. For given traffic demand and network configuration (such as routing scheme, MAC protocol etc.), mesh network yields a particular value of network throughput. Since the traffic always flows between mesh nodes and gateways in a mesh network, we refer to its performability as k -center performability (KCP).

It is apparent that the computational complexity of KCP problem is extremely high due to two reasons. First, as in all performability problems, generating 2^m states is simply formidable. In case of KCP, the problem is especially difficult because the value of m can be very large for even a moderate sized network. The second reason is that even if there exist a method using which we can efficiently generate network states, determining the throughput performance of a network state itself is a known hard problem [80].

Note that Monte Carlo state generation is especially inefficient [75] in estimating $\bar{P}$ because it randomly generates states from the entire state space without any prior knowledge of state's occurrence probability or performance. Due to this, other state generation methods such as *most probable states generation* [70] or *most performable states generation* [81] are also utilized for $\bar{P}$ estimation. The most probable states generation method generates states in order of their occurrence probability, and similarly most performable states generation method generates states in order of their performance.

We devise a method for KCP estimation that combines the advantages of both methods by generating states which have the most impact on KCP in terms of their state probability and performance. In the method, we first find a subset of edges that has the most definite impact

on network performance. This subset is then input to most probable states generation method which yields KCP estimation. Before providing the details of the method, we first see how we can find the throughput performance of a given state of a mesh network efficiently.

5.5.3 Throughput Performance of Mesh Networks

There has been numerous attempts [74, 80, 45, 68, 83] made to precisely find out the throughput capacity of a multi-hop wireless network given the traffic demand of nodes. The key limitations of these approaches are that either they yield an asymptotic performance or their calculation is computationally very expensive even for a moderate sized network. In our case, since the throughput has to be calculated for a large number of states, clearly such methods are not useful. But there is a key difference between the traffic characteristics of general ad-hoc networks and mesh access networks which allows a polynomial time calculation of capacity. Traffic in mesh access network always flows between mesh nodes and gateways as opposed to traffic between random pairs of nodes as in ad-hoc networks. This makes the calculation of the capacity more tractable because the capacity of the network clearly depends on how much aggregate traffic gateways can transfer.

In mesh networks, traffic aggregation near the gateways is always high which results in traffic bottlenecks near the gateways. The collision domains created around each gateway dictates how much traffic demand can actually be satisfied. *The traffic accumulation around the gateways is so high that throughput reductions due to lower spatial reuse in other regions of the network has only a little effect on the overall capacity.* This was first shown by Knightly et al. in [134, 133] for CSMA case, and was later re-validated for TDMA systems by [121].

Formally, let D bits per second be the total expected traffic demand of a mesh network. This is the cumulative demand of all mesh nodes in the network. Since every mesh node forwards its data to its gateway, let D_{g_i} denote the traffic demand associated with gateway g_i . Now, let CD_{g_i} be the collision domain of gateway g_i . The collision domain of a gateway is the largest set of links around the gateway such that every pair of links mutually interfere with each other. Let $|CD_{g_i}|$ denote the size of the collision domain, that is the total traffic of all the links in the collision domain. Now, as described in [121, 134], $|CD_{g_i}|$ is the total traffic in a collision domain out of which D_{g_i} is the useful traffic. Meaning, during the time proportional to $|CD_{g_i}|$, the gateway is either transmitting, receiving or deferring for other transmission in the collision domain, while during the time proportional to D_{g_i} , the gateway is either transmitting or receiving (useful communications). This comparison yields a good estimation of how much wireless bandwidth a gateway utilizes for useful transmissions, which in turn determines the throughput capacity. The ratio $\delta_{g_i} = |CD_{g_i}|/D_{g_i}$ measures how poorly a gateway utilizes the wireless medium for useful transmission.

Figure 5.10: Edges of a WMN can be classified into three sets - X, Y and Z - depending on their interference characteristics

Due to high traffic accumulation near the gateways, the ratio δ_{g_i} is almost always larger than one. Now, if the capacity of the gateway g_i is B_{g_i} bits per second then total aggregate throughput of the mesh network in bits per second is –

$$W = \sum_{i=1}^k \frac{B_{g_i}}{\delta_{g_i}} \quad (5.12)$$

As described in [133, 121], the throughput calculation presented here assumes a fair MAC protocol.

5.5.4 Calculating K-center Performability

In this section, we show how most probable states generation method can be utilized for KCP evaluation. The proposed method of calculating KCP consist of two phases. In the first phase, we identify a subset of edges which are most crucial in determining KCP of a mesh network. This subset of edges becomes the input for most probable states method in the second phase. The method generates relatively fewer but important states which contribute the most towards KCP value due to their occurrence probability and performance. We now discuss the details of both phases in order.

Phase 1: Edge selection

The purpose of edge selection phase is to identify l edges from total of m edges for which the most probable states (MPS) algorithm can be applied. In the states generated by the MPS algorithm, we fix the states of all edges other than these l edges. It is obvious that criteria for

selecting l edges should depend on their expected impact on network performance and their existence probability. To capture these characteristics of edges, let the edge set E of $G_P(V, E, P)$ be divided into three mutually exclusive and exhaustive subsets as below (Fig. 5.10) –

- X : an edge $e_i \in X$ if neither of the endpoints of e_i is a gateway and e_i does not interference with any gateway when active.
- Y : an edge $e_i \in Y$ if neither of the endpoints of e_i is a gateway and e_i interferes with a gateway when active.
- Z : an edge $e_i \in Z$ if one of the endpoints of e_i is a gateway and because of that e_i interferes with a gateway when active.

It is obvious that edges of Z will carry more traffic on an average than edges of Y , and edges of Y will carry more traffic than edges of X in general. Since edges of Y and Z belong to a collision domain, their impact on network performance is also more substantial. Based on this understanding we determine the states of edges of each subset and also find l links for MPS algorithm as shown below –

- $\forall e_i \in X, s_{e_i} = 1$. This means that edges of set X are always in operating state in all network states that are generated by MPS algorithm. This is because these edges have the least impact on network performance as we saw in section 5.5.3. Forcing these edges to be in operating mode allows maximum influx of traffic from all mesh nodes to gateways.

- $\forall e_i \in Y, s_{e_i} = 1$ if $p_{e_i} \geq 1 - p_{e_i}$; $s_{e_i} = 0$ otherwise. This means that edges in set Y are in their most probable state. As we know that these edges have a definite impact on network performance, we ensure that they remain in their most probable state in all network states generated by MPS algorithm, and affect the KCP evaluation only when they are likely to be in operational mode.

- In terms of KCP, the edges in Z are of foremost importance. Since the network throughput is mostly dependent on these edges, choice of l links for MPS algorithm is made from this set. To do so, first we calculate probability weighted interference score I_{e_i} for every $e_i \in Z$. I_{e_i} is calculated as $I_{e_i} = p_{e_i} \times \sum_{e_j \in Z} p_{e_j}$, where $e_i, e_j \in Z$, and e_i and e_j mutually interfere. I_{e_i} score of a link shows the likelihood that the link will be in operational mode and it will interfere with how many other links from Z which are also expected to be in their operational mode. We sort the links of Z in decreasing order of their I_{e_i} scores and create a set L using the first l links. These links are then input to MPS algorithm. This way, links which have the most impact on network performance and state occurrence probability are chosen for MPS algorithm. Also, states of the remaining $Z - L$ links are fixed depending on l links. Let $\rho = \max\{p_{e_i}, e_i \in L\}$. Now, for $e_i \in Z - L$, $s_{e_i} = 1$ if $p_{e_i} \geq \rho$, and $s_{e_i} = 0$ otherwise.

Phase 2: Most Probable States Algorithm

The MPS algorithm presented in [70] sequentially generates the most probable network states in order of decreasing probability. In this work, we utilize this algorithm with l edges found above. Since all other edges in $E - L$ have been assigned a fixed state, MPS algorithm generates states of l edges in each iteration. This means that MPS algorithm assumes as if the network only contains edge set L and generates their states.

Now, for each of the network state generated by MPS algorithm, we find its throughput performance using the method proposed in section 5.5.3. The MPS algorithm generates all $\chi = 2^l$ network states where state occurrence probability ($Pr(S)$) of each network state is determined using states of l links in the network state. Let $F(S)$ be the throughput performance of S . The performability estimate $\bar{P}$ is then calculated as $\bar{P} = \sum_{S \in \mathcal{X}} (F(S) \cdot Pr(S))$.

For efficiency, we terminate the state generation when cumulative probability of generated network states reaches 0.99. As described in [70], the actual efficiency of MPS method depends on the average PQ factor. The average PQ factor is defined as the average of n_{e_i}/m_{e_i} ratio for all $e_i \in L$, where n_{e_i} is the probability that e_i is in its least probable state and $m_{e_i} = 1 - n_{e_i}$. Higher value of average PQ factor shows that the difference between link existence and failure probability is lesser for many links, and more states are required to be generated for cumulative state probability of 0.99. While lower value of average PQ factor shows that first few most probable states are sufficient for cumulative probability of 0.99.

5.6 Analyzing KCA of WMNs

Equipped with KCA and KCP evaluation methods, we now evaluate KCA and KCP of various mesh networks. In this section, we apply the KCA evaluation method (CMCS algorithm) to two existing urban mesh networks. For each network, we calculate the link availabilities as shadowing probabilities using their real-world RF profiles.

5.6.1 KCA of GoogleWiFi

GoogleWiFi [9] is a mesh network deployed in Mountain View, CA (Fig. 5.11a) which consists of approximately 449 mesh nodes and 59 Internet gateways. For determining link availabilities based on shadow fading, we use the data provided in studies [133] and [135]. The studies showed that the network has a path-loss coefficient (η) of 3.7, shadowing factor of (σ) of 8 dB, and reference path loss of 55 dB at 10 meters distance. We choose the receiver sensitivity to be -80 dBm. Given this RF profile and locations of mesh nodes, we apply the KCA evaluation method to GoogleWiFi. The results are presented in Fig.5.12a. For the purpose of understanding, we increase the transmission power of nodes which should increase the KCA of a WMN. It is

(a) GoogleWiFi - Mesh network in Mountain View, CA, Map from [9]

(b) PoncaCityMesh - Mesh network in Ponca City, OK, Map from [20]

Figure 5.11: GoogleWiFi and PoncaCityMesh - two mesh network considered in study

noticeable that GoogleWiFi’s current network topology requires a very high transmission power from nodes in order to achieve even a reasonable KCA. Since maximum EIRP allowed for IEEE 802.11 a/b/g standards is 4 W (36 dBm) in USA, we mark this point in the figure to show that GoogleWiFi achieves KCA as low as 0.3299 at that point. Even though transmissions are not allowed at higher transmission powers, we show these values for the purpose of further understanding. **In order to achieve a KCA of 0.99 (often known as “two nines” of network availability) in GoogleWiFi, transmission power as high as 25 W is necessary.** This being impractical, we will study the alternative designs to achieve a higher KCA in later sections.

An obvious step at this point is to understand the accuracy of KCA evaluation provided by CMCS method. We defer this discussion until Sec.5.9 where we will show the relationship between bounds and confidence intervals of KCA estimate at each point of simulation. We do so because the accuracy of KCA estimate is sufficiently high (with reasonable efficiency) so that the analysis and general discussion presented here stand true. *Also, each of the data point in KCA and KCP analysis takes upto 7 hours of simulation on average.* Further details of these are provided in Sec.5.9.

5.6.2 KCA of PoncaCityMesh

We now evaluate the KCA of another urban mesh network named PoncaCityMesh. It is a mesh network deployed in Ponca City, Oklahoma (Fig. 5.11b) for public Internet access. The network consists of approximately 469 mesh nodes with 60 gateways. The RF profile of the city neighborhood is $\eta = 3.5$, $\sigma = 8$ dBm, and reference path loss of 50 dB at 10 meters distance.

The KCA evaluation is shown in Fig.5.12b. As with GoogleWiFi, PoncaCityMesh also demonstrates a lower KCA. In this case, we also show the transmission power levels necessary to achieve two and three nines of availability. The increase in KCA of PoncaCityMesh as compared to GoogleWiFi can be mostly attributed to a better RF profile of urban neighborhood.

5.6.3 KCA and Deployment Factors

Next step in understanding KCA characteristics of WMNs is to analyze the exact impact of deployment factors on KCA. It was previously shown in [133] that a mesh network topology in which mesh nodes (including gateways) are placed in a square grid, and k centers of the network graph are chosen as gateways can achieve the highest availability and performance compared to other model topologies. By using these topological settings, we now show what exact transmission power and/or node density are necessary in order to achieve a high KCA. *It is obvious that increase of transmission power and/or node density will result in higher KCA*

(a) KCA of GoogleWiFi (Sampled at every 100th mW)

(b) KCA of PoncaCityMesh (Sampled at every 100th mW)

Figure 5.12: K-center Availability of GoogleWiFi and PoncaCityMesh networks

(a) Impact of Tx power and node density on KCA (Sampled at every 100th mW)

(b) KCA within allowable EIRP (Sampled at every 100th mW)

Figure 5.13: Increasing transmission power increases availability; Phase transition width depends on node density

but we are interested in studying their precise values for any given target KCA.

Fig.5.13a shows how KCA varies with varying density and transmission power of nodes. As expected, it shows that increasingly high transmission power is required to achieve a high KCA when the node density is lower. In all cases with grid node placement, we use RF profile of GoogleWiFi's urban neighborhood in KCA evaluation. With consideration of maximum allowable EIRP, Fig.5.13b shows the phase transition behavior of all different densities with maximum EIRP being 4 W.

An optimization problem of designing a mesh network with a certain guaranteed KCA while utilizing minimum resources can be better understood using results of Fig.5.14b. It shows for every power level (or node density) what is the minimum necessary node density (or power level) to achieve a targeted KCA. Even at the maximum EIRP of 4 W, it can be observed that number of nodes necessary per km^2 is very high. Also, the required node density value increases with increase in targeted KCA. Guidelines such as the one presented in [29] suggest that current deployment techniques typically uses 8 to 10 nodes per km^2 which is clearly insufficient as per our KCA analysis. Apart from this, real world node placement is unlikely to follow a grid placement, and the added perturbation further decreases the KCA as compared to grid placement. **Our KCA analysis shows that a grid network with 20 nodes per km^2 with each node operating at maximum EIRP yields a network in which mesh nodes are connected to gateways only 90% of the time. To increase the availability upto 0.9999 as many as 40 nodes per km^2 is necessary. The number is likely to be even higher in real world deployments that can not follow a grid placement.**

One of the parameters which we did not vary previously in KCA evaluation is receiver sensitivity. On one hand, a higher receiver sensitivity is necessary for links to operate at a higher physical layer data, while on the other hand, increase of receiver sensitivity results in decrease of communication range of a node which in turn reduces the KCA value. This is demonstrated in Fig.5.15 where we vary receiver sensitivity of nodes while fixing the node density to 30 nodes per km^2 . It is observed that phase transition widths increase with the increase in receiver sensitivity, and a much higher transmission power or node density is necessary if we want to operate the links of a mesh network at higher link rates.

The requirement of higher transmission power in order to design a network with lower node density or higher node density but higher link rates come at a penalty of increased interference. In general, the increased transmission power reduces the throughput performance of a network due to increased interference. This way, KCA and network performance can be at trade-off and it might be very difficult to design a highly performable network with high KCA value. We try to understand this by exploring KCP of WMN next.

(a) Minimum Tx-power/density required for a target KCA

(b) Minimum Tx-power/density required for a target KCA

Figure 5.14: Minimum Tx power and node density increases sharply with increase in target KCA

Figure 5.15: Higher receiver sensitivity reduces communication range of nodes which in turn reduces graph density and KCA

5.7 Analyzing KCP of WMNs

Increasing transmission power and/or node density increases KCA but can reduce the throughput performance due to increased interference. We analyze this trade-off next by understanding the relationship between KCP and the deployment factors.

5.7.1 KCP and Deployment Factors

We first analyze the KCP of WMNs where mesh nodes are placed in a square grid, and then evaluate the KCP of GoogleWiFi and PoncaCityMesh. In all cases, a total of 300 Mbps traffic is inserted in the network which is uniformly divided among the mesh nodes. Fig.5.16 shows the how KCP changes with varying node density and transmission power. The main observations are as follows -

- (1) In general, for every node density, KCP first increases with increase in transmission power. This is due to the fact that availability of mesh nodes increases in this initial period which allows more and more nodes to transfer their data to gateways. This increase in throughput performance yields an increasing KCP initially. Further increase in transmission power results in decrease of KCP because of increasing interference among the nodes which reduces the

Figure 5.16: Impact of node density and transmission power on network KCP

throughput performance. **Here, availability of mesh nodes is still higher but the drastic decrease in the performance results in lower KCP.**

(2) **KCP shows a saw-tooth wave like pattern with increase in transmission power.** This is because throughput performance of a WMN displays a behavior similar to a step function where the performance decreases sharply and then remains unchanged until another subsequent decrease. The sharp decrease is due to fact that at a certain transmission power level, interference collision domains of nearby gateways start overlapping with each other. The performance remains unchanged until the subsequent overlap of collision domains. During this phase where throughput performance is unchanged, the availability still increases with increase in transmission power. This results in increase of their joint metric – KCP in this region with saw-tooth-like overall behavior.

(3) Note that **decrease in KCP is much faster for higher node densities.** This is due to the fact that the diminishing effect of interference is much worse at higher density, and throughput performance starts dropping at lower power levels yielding lower KCP value.

(4) A interesting observation is that **absolute values of maximum KCP remain comparable even at very high density values.** This is because higher density yields a lower performance due to interference but the availability with which it is delivered is higher for them. This is an especially important result because it differs from the conventional understanding that higher node density yields lower network throughput ([74]). When the design strategy shifts from performance to performability, in fact higher node density can be beneficial.

(5) Note that KCP does not become zero even at very low transmission power. At this point, almost all mesh nodes are disconnected from gateways and are unable to transfer any data. But since the **gateways also act as access point to clients, their data gets through Internet even if no other mesh nodes are connected.**

For a given receiver sensitivity, links operate at a specific data rate in absence of any interference. Increasing receiver sensitivity increases link data rate and network performance but reduces the network availability. This motivates us to study the impact of receiver sensitivity on KCP. As the first step towards studying performance-degradable network, we assume that the links are not performance-degradable. This means that a link provides a specific data rate only when sensitivity requirement is met, and is denoted dysfunctional otherwise, even though it can provide a lower data rate in its degraded state. We leave this case of degradable links for future study. Here, we fix the node density to be 15 nodes per km^2 and vary the transmission power and receiver sensitivity. We use the parameters of 802.11a for mapping receiver sensitivity to its corresponding data rate. Fig.5.17 shows that in fact increasing receiver sensitivity results in increased KCP due to sharper increase in performance but not so sharp decrease in availability.

Figure 5.17: Higher receiver sensitivity increases KCP because of sharper increase in performance while not so sharp decrease in availability

5.7.2 KCP of GoogleWiFi and PoncaCityMesh

We now evaluate KCP for GoogleWiFi and PoncaCityMesh network. The results are shown in Fig.5.18a and 5.18b respectively. The general behavior discussed in case of grid topology remains more or less similar for both the networks. One of the reason PoncaCityMesh achieves better KCP is because it contains more gateways compared to GoogleWiFi.

5.8 Designing WMNs with high KCA and KCP

The objective behind studying KCA and KCP of WMNs is to design a mesh network that can guarantee a certain KCA and/or KCP. One or both of these metrics can be used by network designers to establish useful SLAs with service providers. We consider three cases with different design objectives -

(1) In certain cases, it is necessary that a mesh network provides high connection robustness (high KCA) but some variations in performance are easily acceptable (low KCP). There can be many applications that can use such settings where having a connection is more important than the performance the connection can provide. For such design objective, **minimum node**

Figure 5.18: KCP of (a) GoogleWiFi (b) PoncaCityMesh

density that can achieve the target KCA using maximum allowable EIRP is the most cost-effective design alternative. Utilizing maximum EIRP may incur performance penalties (lower KCP) but ensures high KCA. As an example, for RF profile considered in Fig.5.14b, if “three nines” of availability is required, a grid mesh with nearly 35 nodes per km^2 is necessary and sufficient.

(2) In cases where a mesh network is necessary to provide a certain target performance robustness (KCP), it is necessary to find a combination of node density and transmission power that can achieve the target KCP. As an example, for RF profile and traffic requirement in consideration in Fig.5.16, if the target KCP requirement is 100 Mbps, then it is necessary and sufficient to design a grid network with 40 nodes per km^2 and operate the nodes at 2 W of transmission power.

(3) Third and the most interesting case is to design a mesh network that operates at highest possible KCA and KCP. It can be observed from Fig.5.13a and Fig.5.16 that for any given node density, increasing transmission power increases KCA and KCP upto a certain point. Beyond this, increase of transmission power may or may not increase KCA but starts decreasing KCP. This trade-off shows that in fact it is challenging to choose a transmission power level that can

Figure 5.19: Tx-power and/or density necessary to achieve a given KCA or KCP; For the grid topology cases studied along with the RF settings, maximum KCP is achieved when Tx power/density is sufficiently high to achieve KCA of 0.9

maximize both KCA and KCP.

For further understanding, we plot the data of Fig.5.14b (with curve smoothing applied) along with the data extracted from Fig.5.16 which shows the power level at which each density achieves maximum KCP. This data is shown in Fig.5.19. We can observe that **in fact a mesh network achieves maximum KCP when its KCA is between 0.9 to 0.99**. Of course, this results are restricted to the case of given RF profile square grid placement of mesh nodes.

At higher densities, the maximum KCP is achieved at a power level necessary for achieve KCA of 0.9 while at lower densities, the maximum KCP is achieved at a power level necessary to achieve KCA of 0.99. **One important observation is that at lower densities (for 10, 20, 30 and 40 cases) minimum power necessary for higher KCP occurs after first sharp decrease of KCP (Fig.5.16).** The sharp decrease occurs due to overlapping of collision domains of nearby gateways at high power levels. This means that in fact it is advisable to operate the network with overlapping collision domains of gateways because the availability benefits of doing this is more compared to performance penalties associated with it.

5.9 Efficiency and accuracy analysis of KCA and KCP evaluation

Now we validate our claims about accuracy and efficiency of KCA evaluation method. First, Fig.5.20(a) shows the nature of edge packing bounds along with the actual value of KCA estimated by CMCS method. Fig.5.20 shows the results for node density of 40 nodes per km^2 . The bounds indicate the amount of reduction in search space when executing the Monte Carlo simulation. This is reflected in Fig.5.20 (b) and (c) which show the number of samples necessary and time taken for KCA estimation respectively. The simulations were run on a desktop computer with 1.6 GHz processor and 1 gigabytes of memory. As expected, simulation time and number of samples are a function of bounds as well as number of edges in the networks.

It is obvious that the efficiency of CMCS procedure also depends on the size of the network (node density and number of edges). To understand this, we normalize the required time of simulation using the number of edges in the network. The results are shown in Fig.5.21. The transmission power level at which the simulation time is the maximum increases with decrease in density. This is because the phase transition as displayed in Fig.5.13b occurs at higher power levels for lower density.

Lastly, we evaluate the efficiency of KCA estimation method. We set the accuracy level of CMCS method to be 10^{-5} . Fig.5.22 shows the relation between (upper bound - lower bound) and (upper confidence limit - lower confidence limit). The confidence intervals are calculated using the method suggested in [61]. As the bounds become tighter, the corresponding confidence intervals also shrink.

To examine how accurate is the proposed KCP evaluation method, we apply it on a smaller network with 20 nodes, 40 links and 100 Mbps of input traffic. We generate all ($2^{40} \approx 10^{12}$) network states and calculate the exact value of $\bar{P}$. We also apply the proposed KCP estimation method with $l = 20$. The results are shown in Fig.5.23. It can be observed that the proposed method yields a good estimate of the actual KCP value. Also, the time requirement of proposed method is significantly less (nearly 26 hours in worst case) than entire state space generation (approx. 198 hours in worst case). Since the presented comparison is only for a small network, we don't claim that the same holds for larger networks. We are unaware of any better method of KCP evaluation that can be used for comparison, which we consider to be one of the limitations of our work.

We now evaluate the efficiency of the proposed KCP estimation method. As mentioned before, time requirement of MPS algorithm depends the average PQ factor. For node density of 60 nodes per km^2 , Fig.5.24 shows the average PQ factor and the time required for KCP estimation. Higher value of average PQ factor shows that more network states are required to be generated for a cumulative state probability of 0.99.

Figure 5.20: Efficiency of CMCS method: (a) Edge-packing bounds (b) number of samples required (c) simulation time; Fitted lines plotted in (b) and (c) show the overall trend; Curves calculated using Cubic spline

5.10 Concluding Remarks

In this chapter, we defined connection and performance robustness for wireless mesh networks. We developed efficient methods that can estimate both KCA and KCP for large urban-scale mesh networks. With hundreds of hours simulations, we showed that how current mesh network can not deliver a high KCA and KCP to its users. We also outlined new design policies that

Figure 5.21: Maximum time taken for KCA estimation depends on the phase transition width of each density

Figure 5.22: Accuracy of KCA estimation method

can be followed in order to design mesh networks that have high KCA and KCP.

Figure 5.23: Accuracy of KCP estimation method

Figure 5.24: Efficiency of KCP estimation

Chapter 6

Increasing Network Utilization and Fairness in Wireless Networks

We discussed various design issues of wireless networks such as throughput capacity (Chapter 3), load balancing (Chapter 4) and service continuity (Chapter 3) in previous chapters. While evaluating the KCP, we used an ideal case estimation of throughput performance that enforces fairness in network resource allocation. This allows faster computation (especially necessary in large state space), it is difficult to implement in real-world using realistic MAC protocols such as CSMA-CA. To address this, we now turn our attention to fairness and network utilization issues in mesh networks. We describe the inherent unfairness that is present in mesh network traffic pattern and propose solutions using utility maximization framework.

First, we show that the back-pressure based scheduling policy originally proposed by Tasoulas et al. in [149] has the potential of solving many fairness and network utilization related problems of wireless multi-hop networks. We also describe how the policy can be adapted in random medium access protocols such as CSMA/CA using MAC layer priorities. Here, MAC priorities are used to provide differentiated services to nodes depending on their queue backlogs. Using this implementation of back-pressure framework, we demonstrate that it is indeed possible to relieve the spatial bias of wireless mesh networks. This means that nodes farther away from the gateway can also achieve comparable throughput. The improvement is due to the fact in back-pressure scheduling, (per-destination) queues compete for medium access as opposed to links which ensures fair per-flow medium utilization.

We show next that even though the MAC priority based implementation of back-pressure scheme on CSMA/CA works well in experiments to emulate back-pressure scheduling, they perform poorly with realistic Internet-type traffic where there is a large variation in packet sizes. To address this, we propose packet aggregation based back-pressure scheduling which aggressively increases the rates at which back-logged queues are served. Different from other aggregation

schemes, the presented scheme utilizes the back-pressure principles for determining when and how much aggregation is performed. We show that this results in increased service rates of back-logged queues which in turn results in high network throughput and utilization. We verify our scheme using simulations and show that it achieves significant performance improvements as compared to the original scheme.

Lastly, we design a cross-layer channel width assignment scheme that adapts the width according to the backlog of link-layer queues. We leverage the benefits of varying channel widths while adhering to the invariants of back-pressure utility maximization framework. The presented scheme not only improves throughput and network utilization but also ensures bounded buffer occupancy and fairness.

6.1 Spatial Bias Problem in Wireless Mesh Networks

Numerous research studies [67, 66, 127] have identified the important issue of unfair resource allocation in wireless multi-hop networks. Specifically, location of nodes in flows and their interference relationship can give rise to a spatial bias towards certain flows compared to others. This results in severe unfairness among throughput of flows where a few of the flows can have very high network resources (and high throughput) while others starve for useful bandwidth. As shown in [67, 66, 127], the issue of fairness can be worse when the nodes use random medium access mechanisms such as CSMA.

In case of wireless mesh networks, the unfairness in resource allocation is introduced by the spatial orientation of nodes. This means that nodes that are closer to a gateway can achieve a larger portion of gateway bandwidth as compared to nodes that farther away from the gateway. Also, as the demand of nodes closer to gateway increases, the apportioned bandwidth of distant multi-hop nodes further decreases. To further understand this, we use an example network (shown in Fig. 6.1a) of a chain topology that contains two mesh nodes and a gateway. The distance between subsequent nodes is 80 meters. In the resultant topology, node B can not reach the gateway node G directly, and utilizes node A to relay its traffic.

We use network simulator NS-3 [17] to implement the example network where each node has an IEEE 802.11a radio and link data rate is fixed to 12 Mbps. The following three scenarios are studied using the simulations. The scenarios are shown in Fig. 6.1.

1. Node A inputs 12 Mbps of traffic for gateway G (Fig. 6.1b)
2. Node B inputs 12 Mbps of traffic for gateway G (Fig. 6.1c)
3. Node B inputs 12 Mbps of traffic for gateway G while Node A's traffic demand for node G increases from 1 Mbps to 12 Mbps - in steps of 1 Mbps (Fig. 6.1d)

Figure 6.1: A chain topology of wireless mesh network that demonstrates the spatial bias in resource allocation

We now show the throughput achieved by nodes in each scenario.

1. In Scenario 1, we observed that node A achieves a throughput of nearly 9 Mbps.
2. In Scenario 2, node B achieves a throughput of 4.3 Mbps. The reduction is attributed to an additional hop that the data from node B has to traverse to reach G.
3. The results of Scenario 3 are presented in Fig. 6.2. In scenario 3, it is surprising to observe that when two flows contend for gateway resources, flow originating at a single hop neighbor holds priority over multi-hop flows. As the input rate of node A increases, the throughput of Node B quickly drops while flow from node A captures most of the gateway bandwidth.

The problem of unfairness introduced by the spatial bias can be worse when more realistic topologies and their interference relationships are considered. In the following, we show that back-pressure network utility maximization framework (initially proposed for wired networks by Tassiulas et al. [149]) can be used to improve the fairness among flows in wireless mesh networks. We first provide an overview of the back-pressure framework, and then demonstrate how it can be used for improving fairness in WMNs.

Figure 6.2: Throughput of two-hop node decreases quickly as the input rate of one-hop node increases

6.2 The Back-pressure Framework

The central idea of back-pressure scheduling policy is that contention among the links should be resolved by scheduling the link which has the largest product of queue differential backlog between its endpoints and transmission rate at which the links can be served. In a perfectly time-slotted medium access mechanism such as TDMA, this will result in optimal throughput of flows while guaranteeing queue stability (ingress traffic to a queue never exceeds its egress traffic). The utility maximization framework initially proposed in [86] shows that injection rates of flows should be chosen such that aggregate utility of the flows is maximized. Here the utility of flow represents a desirable effect on the network achieved by a particular rate of the flow. It was shown in [50, 59, 99, 112] that back-pressure scheduling and utility based rate control together can solve the global problem of network utility maximization.

The back-pressure framework consists of two parts: a link scheduling strategy based on back-pressure and a rate control module for network utility maximization.

Back-pressure scheduling: Back-pressure based link scheduling policy was originally proposed by Tassiulas et al. in [149]. Let's represent the network under consideration using a graph $G = (V, E)$. Let f denote a traffic flow from source node $s(f)$ to destination node $d(f)$ and F

be the set of all flows currently active in the network. Let $l(u, v) \in E$ denote a link between node u and v , and $R_{l(u, v)}$ be the transmission rate of link $l(u, v)$. Transmission rates of all links in E are presented by $\Gamma = \{R_{l(u, v)}, l(u, v) \in E\}$. Let χ be the set of all possible combinations of rates at which links can operate.

Let us assume only for now that the transmission time is divided in equal sized time slots. Every node $u \in V$ maintains a separate queue for destinations of all flows in F . These queues at each node are also known as per destination queues (PDQs). Packets received by u for a flow f destined to $d(f)$ is stored in the queue $Q_u^{d(f)}$ until further forwarding decisions are made. Let $|Q_u^{d(f)}(t)|$ denote the size of the PDQ maintained at node u for destination $d(f)$ at time t . Every node shares its PDQ length information with all its neighbors at the beginning of time slot t . Every node then calculates its differential backlog as compared to its neighbors for every flow destination. That is, a node u calculates $D_{l(u, v)}^{d(f)}(t) = |Q_u^{d(f)}(t)| - |Q_v^{d(f)}(t)|$ for all $l(u, v) \in E$ and all $f \in F$. Now, for every link $l(u, v) \in E$, let

$$\Delta_{l(u, v)}(t) = \max_{f \in F} \left(D_{l(u, v)}^{d(f)}(t) \right) \quad (6.1)$$

Back-pressure scheduling suggests that Γ at time t should be chosen such that –

$$\Gamma(t) = \max_{\Gamma \in \chi} \sum_{l(u, v) \in E} (R_{l(u, v)} \Delta_{l(u, v)}(t)) \quad (6.2)$$

It was proved in [149] that a routing/scheduling policy that can achieve a solution of Equ. 6.2 is throughput optimal. This means that it stabilizes the queues at every node while supporting the largest possible capacity region. A capacity region (C) of a network is defined as the set of all flow rates which are supportable by the network. Due to link interference constraints, the above mentioned problem is proven to be NP-hard in wireless networks. Also, its distributed implementation imposes many more challenges in design of a routing/scheduling scheme for wireless networks.

Rate control: The back-pressure scheduler determines the transmission rates at which packets are served at links so that the queue sizes at nodes remain bounded while maximizing the achievable throughput. The other part of the back-pressure framework performs the rate control of the flows. The flow controller determines the rate at which flows can inject the packets in the network. In back-pressure framework, the flow controller determines the input rates of flows based on the state of queues at each intermediate node. The PDQ information is utilized by the flow controller to adjust the flow input rates in a way that a desirable network-wide objective is optimized. In a seminal work, [86] showed that such flow/congestion control can be viewed as primal-dual algorithm for the solution of network utility maximization problem. This was further elaborated in [32] in context of the back-pressure framework which we describe

next.

Suppose that each flow f from $s(f)$ to $d(f)$ has a utility function associated with it. This utility function $U_f(x_f)$ is a function of the rate x_f of the flow f . Let us represent input rates of all flows using $\psi = \{x_f, f \in F\}$. The utility maximization problem suggests that the flow rates should be chosen such that their aggregate utility is maximized, that is –

$$\max_{\psi \in C} \sum_{f \in F} U_f(x_f) \quad (6.3)$$

A flow controller that can maximize the aggregate utility was presented in [32]. It suggests that in each time slot t , source $s(f)$ of a flow f injects a packet in the network if and only if

$$U'_f(x_f(t)) - \beta Q_{d(f)}^{s(f)}(t) > 0, \quad (6.4)$$

where U'_f is the first derivative of utility function of the flow and β is a small constant. The above condition controls that a packet should be injected in the network by a flow only if the eventual utility benefit of the insertion is larger than a constant times the size of source node PDQ. That is when intermediate nodes of a flow are sufficiently back-logged, the source node pushes more packets in the flow at a slower rate. The back-pressure scheduler ensures that queue backlog status of intermediate nodes is reflected back at the source node which then performs the rate control to accordingly change the flow input rate.

This way, the back-pressure based link scheduling controls which links should be transmitting at what rate, and the rate control module manages the rates at which the packets are injected by the flows. Both together can solve the network-wide utility maximization problem to yield a throughput-optimal solution.

6.2.1 Back-pressure Framework and CSMA/CA MAC

The fundamental challenge with back-pressure framework is that solution of the underlying scheduling strategy is NP-hard [69]. Also, since it was proposed for a centralized, synchronized and time-slotted system, a distributed implementation which can achieve even an approximation is very difficult to develop. Recently, [32, 155] have attempted to incorporate back-pressure based scheduling in random medium access protocols such as CSMA/CA. These protocols try to approximate the performance of the ideal back-pressure scheduler by prioritizing the frame transmissions according to differential backlogs of queues. Here, every node in the network maintains a per destination queue (PDQ) and the packets destined to a particular destination are stored in the PDQ of that destination until further forwarding decisions are made. Now, nodes share their PDQ information with their neighbors, and this information is utilized by every node to calculate differential backlogs of its PDQs. The differential backlog of a PDQ at

a node is equal to the size of the PDQ minus the size of the PDQ of its upstream neighbor towards the destination. To emulate the back-pressure scheduling, packets of the PDQ which has the highest differential backlog (highest back-pressure) in the neighborhood are given the higher chances for transmission. This way, the likelihood that packets are transmitted from a particular PDQ at a node is proportional to its differential backlog compared to the differential backlogs of PDQs of all nodes in the neighborhood. This prioritization quickly moves the traffic from long back-logged queues to shorter queues achieving an improved throughput and a better overall stability of queues.

As mentioned before, in back-pressure scheduling every node maintains a PDQ for every flow passing through the node. Note that we assume a fixed routing policy in this work where routes are calculated in advance for every flow and packets are forwarded on these routes only. This is different from an ideal back-pressure strategy where the routing is adaptive, and forwarding decisions are made on packet by packet basis. In the ideal scheme, every neighbor of a node depending on its size of PDQ is a potential candidate for forwarding the packet [161]. Since our objective is to explore packet aggregation with back-pressure strategy, we restrict our focus to fixed routing and leave the adaptive routing extension to future work.

Due to fixed routing, every node has a unique upstream neighbor for every flow passing through it. Now, the differential backlog at a node u for flow f can be presented as $D_u^{d(f)}(t) = |Q_u^{d(f)}(t)| - |Q_v^{d(f)}(t)|$, where v is next hop neighbor of node u for flow f . Each node maintains following information ([155, 32]) in order to correctly execute the joint back-pressure and aggregation scheme –

1. Per destination Queue (PDQ) – a separate queue for each destination of flows passing through the node. Every packet (generated at the node or received from downstream neighbor) is stored in the PDQ of corresponding destination until further forwarding decisions are made.
2. Urgency Weight – every PDQ has an urgency weight associated with it. The urgency weight is the differential backlog which equals to the backlog of the PDQ subtracted by the backlog of the PDQ on the next hop neighbor towards the destination.
3. Urgency Weight State (UW state) – along with maintaining PDQs and their corresponding urgency weights, every node knows the PDQ ID, node ID and urgency weight of the PDQ which has the maximum urgency weight in the neighborhood. The same is also maintained for the minimum urgency weight PDQ of the neighborhood. This information determines a node's UW state with respect to its neighbors. To implement this, every node shares its PDQ information with its neighbors by using separate messages or piggybacking techniques.

Figure 6.3: An example topology showing two flows that share a link in their routing path

4. Source List – source node of every flow which generates packets first stores the packets in a per destination source list. Once the rate control is performed then only the packets are added to the corresponding PDQ at the node. Different from the PDQs which are maintained at all nodes, per flow source lists are only maintained at the source nodes of the flows.

In a back-pressure scheduling implementation without aggregation ([155, 32]), when a node sends out a frame from a PDQ, it first determines its MAC layer priority. The MAC priority is essentially determined by comparing the urgency weight of the PDQ to the UW state of the node. In essence, this compares the differential backlog of the PDQ with the differential backlog of other PDQs in the neighborhood and assigns it a MAC priority based on it. Packets of the PDQ which has the highest urgency weight in the neighborhood are assigned the highest MAC layer priority for faster transmissions. Here, it is assumed that MAC layer is able to provide differentiated levels of service. In our experiments, 4 MAC layer priorities are considered starting from 0 to 3. Packet sent out with higher priority has higher chances of accessing the channel as compared to the packets sent out at lower priorities. CSMA/CA MACs like 802.11e provides such differentiated service levels which we also use in our simulations. This prioritization of transmissions tries to serve the longer queues with higher service rates which is the ultimate objective as described in Equ. 6.2.

Fig. 6.3 shows an example network with two flows sharing a link in their routing path. Fig. 6.4 shows the PDQs that result at source nodes (A and B) and intermediate nodes (C and D). Note that since nodes C and D are part of both traffic flows, each of them maintain two separate PDQs for destinations E and F. The urgency weight of every PDQ can be calculated

Figure 6.4: Per-Destination Queues (PDQs) maintained by each node in network. Node C and D maintain two PDQs for two flows passing through them

Figure 6.5: Urgency weight of a PDQ is calculated by subtracting uplink PDQ size from its own size

Figure 6.6: Rate control module controls how and when packets are inserted from source list to PDQ, the packets are stored in source list until the rate control decision is made

Figure 6.7: A five node chain topology with four mesh nodes and a gateway

by subtracting backlog of uplink PDQ from its own backlog. This is shown in Fig. 6.5 for node E. The source of every flow maintains an additional list (called source list) which stores the packets generated by any application. Depending on the size of PDQ, its urgency weight and rate control, packets are transferred from source list to PDQ. As shown in Fig. 6.6, an application at node A inserts packets to source list, and packets are moved from source list to PDQ only when the rate control permits.

6.3 Addressing Spatial Bias Problem using Back-pressure Framework

We now return to the issue of spatial bias in resource allocation in wireless mesh networks. It is shown here that when each mesh node implement back-pressure scheduling and rate control policy, it is in fact possible to relieve the bias and allow the nodes to achieve a fair share of network resources.

Table 6.1: Throughput of mesh node in a chain topology without inter-flow interference

Flow	Hop-distance	Throughput (Mbps)
A to G	1	9.04
B to G	2	4.43
C to G	3	2.57
D to G	4	2.21

To investigate why and how back-pressure framework can provide fairness among spatially biased flows, we take an example of a 5 node chain topology. The topology is shown in Fig. 6.7. First, we consider a scenario in which only one mesh node sends data to the gateway. In this case, there is no inter-flow interference since there only one active flow in each case. The performance decrease with increasing number of hops is due to intra-flow interference where two links of a flow can not be scheduled together due to their mutual interference. Table 6.1 shows the throughput of each node when it sends data to the gateway. As before, we use 802.11a radio at every node and set the link data rate to be 12 Mbps. Every node inserts 12 Mbps of data. The simulations are performed using NS-3.

We saw in Fig. 6.2 that when there is inter-flow interference, node closer to gateway dominates the network resources. This is shown in Fig. 6.8. In this case, node A and node B both insert data at 12 Mbps destined to gateway G. In the case when there are no PDQs implemented and inter-flow interference exists, node A gets most of the network bandwidth. On the other hand, when back-pressure framework is implemented using PDQs, node B's throughput improves as compared to node A. This yields an improved fairness among flows. It is worth noting that node B's throughput is still lower than node A but the reason for this is not inter-flow interference with node A's flow but intra-flow interference between links of node B's flow. For a reasonable comparison, we show throughput of node A and node B in absence of inter-flow interference. This is mainly because any mechanism that does not deal with intra-flow interference can not achieve a better throughput.

To understand why PDQs can relieve the unfairness issue, we demonstrate the PDQs in Fig. 6.9. It can be observed that now one PDQ at node B and two PDQs of node A are in single collision domain. This way, whenever node A increases its input rate (rate at which packets are transmitted from source list to PDQ) and in turn achieves increased medium access, the urgency weight of PDQ at node B quickly increases. This is because node B's PDQ at node A starves for medium access. This results in subsequent decrease of node A's input rate. Also, packets from node B's PDQ are now transmitted at a MAC priority and node B's PDQ at node A quickly fills up. This in turn improves its transmission opportunity to gateway G. The

Figure 6.8: Back-pressure framework can achieve improved fairness and relieve spatial bias in WMNs

process returns to improved access of node A's PDQ as soon as its urgency weight increase beyond urgency weights of other PDQs. The process constantly moves back and forth between PDQs achieving a fair medium access to all flows.

We now show the same results for 3 and 4 hop flows in Fig. 6.10 and Fig. 6.11 respectively. It can be observed that in case of 4 hops, node D can not achieve any throughput without PDQ strategy. In cases with PDQs, nodes even at 3 and 4 hops achieve a reasonable throughput. The reason it can not achieve throughput values closer to no inter-flow interference cases is because the CSMA/CA implementation of back-pressure framework using MAC priorities acts largely as a feasible heuristic and not an optimal solution.

Figure 6.9: Back-pressure framework coordinates the input rate from source list to PDQs and medium access of PDQs which can in turn achieve a fair medium utilization among mesh nodes

Figure 6.10: Back-pressure framework can achieve improved fairness and relieve spatial bias in WMNs

(a) Node A, B, C and D send data to gateway G

(b) Using PDQs improve fairness among flows

Figure 6.11: Back-pressure framework can achieve improved fairness and relieve spatial bias in WMNs

(a) A grid mesh network with 24 mesh nodes and 1 gateway

Figure 6.12: A grid network of mesh nodes in consideration

(a) Uplink throughput of mesh nodes - input traffic 250 Kbps

(b) Downlink throughput of mesh nodes - input traffic 750 Kbps

Figure 6.13: Utilizing PDQ framework in a grid wireless mesh networks with one gateway

Since the real world topologies are more complex than a chain, we next study a 25 nodes grid network with one gateway as shown in Fig. 6.12a. We consider both uplink and downlink traffic where each node sends 250 Kbps of data to the gateway while receiving 750 Kbps of data from the gateway. The per node throughput is shown in Fig. 6.13a (uplink) and 6.13b (downlink). When back-pressure framework is utilized, nodes farther away from the gateway also achieves reasonable share of network bandwidth. For the case where no PDQs are used, these nodes are starved since most the of the bandwidth is occupied by the nodes closer to the gateway. The four nodes that achieve high throughput in non-PDQ case are the node that are one-hop neighbors of the gateway. These nodes also achieve a high throughput in PDQ case but the dis-proportionality in bandwidth distribution is less severe.

6.4 Improving Effectiveness of PDQs using Packet Aggregation

The idea of using different MAC layer priorities for PDQs with different back-pressure works well in imitating the ideal back-pressure scheduling over CSMA/CA. Even though this enables a distributed implementation, it does not guarantee that only the frames from maximum back-logged queue are being transmitted at any given time. This is because MAC priorities themselves are implemented by modifying the size of the contention window from which the back-off times are randomly chosen. A higher MAC priority frame uses a shorter random back-off time before being transmitted, and it is possible that frames from queue with lower differential backlog get transmitted before frames from queue with higher differential backlog. This problem of not serving the most back-logged queue with the highest possible rate is further aggravated by the fact that most of the packets in last mile networks such as wireless mesh networks are very small in size. [148, 110, 79] show that application layer traffic and TCP acknowledgments account for more than 70 to 80 percent of total traffic where packet sizes are lesser than 100 bytes. With such small packet sizes, time required for medium access and header/trailer overheads adversely affect the overall performance. In case of prioritized frame transmissions, this further reduces the chances that the most back-logged queue is obtaining the maximum possible medium access. Even if the packets are being transmitted from that queue, additional time required for medium access before transmitting every small packet accumulates to a large waste of available air time. Both these factors reduce the rates at which back-logged queues are served which in turn reduces the throughput and network utilization.

In this section, we propose utilizing packet aggregation in the back-pressure framework. The objective is to increase the throughput while maintaining the inherent properties and benefits of back-pressure scheduler. The central idea is to take advantage of packet aggregation for improving the rates at which the back-logged queues are served. Different from other packet aggregation schemes ([79, 89, 128, 64, 132, 162]), the presented strategy utilizes the back-pressure invariants to guide when and how much aggregation is performed. Specifically, when a queue has the highest differential backlog in the neighborhood, instead of transmitting all its head of line packets one by one, the proposed scheme aggregates the first few packets in a large MAC frame which is then transmitted with the highest MAC priority. The number of packets that are aggregated depends on maximum allowable MAC frame size and the differential backlog of the queue. The proposed scheme attempts to reduce the size of the back-logged queues more aggressively which results in their faster service rates. Since the back-pressure policy is utilized to perform the aggregation, the presented scheme preserves the network utility and fairness advantages of the back-pressure policy while yielding an improved throughput performance. This leads to a closer approximation to the optimal solution of back-pressure problem (formally described in section 6.2). Apart from throughput improvements, aggregation based back-pressure

solution reduces the end-to-end delay of packets dramatically which is especially important in delay-constrained applications. We test our scheme using NS-3 and OPNET simulations to verify its performance. It is observed that the aggregation scheme outperforms the most current implementation of back-pressure scheduler which does not utilize packet aggregation.

6.4.1 Back-pressure and Packet Aggregation

The service rates of back-logged queues can be further increased if more and more packets are transmitted from the queues with higher urgency weights. Note that the implementation of back-pressure strategy without aggregation tries to maximize the chances that medium is occupied by the packets transmitted from the longer queues, but it does not guarantee to do so. Since a large number of packets are very small in size and medium access has to be initiated before every transmission, it is not guaranteed that the packets of the longest queue in a neighborhood receives the highest possible service rate from the medium. Instead if the packets of the longest queues are aggregated before their medium access and eventual transmission, more packets can be sent out from the backlogged queue in each medium access. This eliminates the additional time required for medium access by every small packet and increases the total air time utilization by longer back-logged queues. This increases the service rates of back-logged queues which in turn maximizes the objective function presented in Equ. 6.2. It is obvious that back-pressure with aggregation is also an approximation of the optimal solution to Equ. 6.2 but is closes the gap further towards the optimal solution by improving on any currently available scheme.

Now we describe how exactly packet aggregation is performed while using back-pressure invariants as guidelines. Aggregation based PDQ scheduler at every node de-queues the head of line packets from PDQ with the highest urgency weight. The node then performs the check whether the PDQ is in fact the highest urgency weight PDQ in the entire neighborhood. If so, it de-queues more packets from the PDQ. It continues to do so until the PDQ retains the highest urgency weight in the neighborhood or until sum of the size of all the de-queued packets is less than the maximum allowable MAC frame size. All the de-queued IP packets are then bundled in a large MAC frame of aggregated packets. The MAC frame is then assigned a MAC priority depending on the current UW state of the node. Since the PDQ from which the packets were de-queued had the highest urgency weight in the neighborhood, it is also likely that the MAC priority of the frame of aggregated packets will be the highest too. Because of aggregation the total time taken to transmit these set of packets will be reduced as compared to their individual transmissions. This increases the service rate of the PDQ with highest urgency weight in the neighborhood yielding a closer approximation of Equ. 6.2. The complete procedure of aggregation and back-pressure scheduling is described in Algorithm 2.

Rate control: While the back-pressure scheduling and aggregation is performed at every

Algorithm 2 Packet Aggregation + Back-pressure Scheduling

```
maxAggSize  $\leftarrow$  Maximum allowable size of a MAC frame;  
size  $\leftarrow$  0;  
q  $\leftarrow$  PDQ with the highest urgency weight;  
repeat  
  Dequeue the HOL packet p from PDQ q;  
  Add p to the packet aggregate;  
  size := size + sizeof(p);  
until size  $\leq$  maxAggSize AND PDQ q has the highest urgency weight in the neighborhood  
Determine MAC priority of the aggregated packet using Determine-MAC-priority(q);  
Transmit the packet with the MAC priority;  
Update the size and urgency weight of PDQ q.  
  
  Determine-MAC-priority(q)  
    numLevels  $\leftarrow$  Number of MAC priority levels;  
    max  $\leftarrow$  Maximum urgency weight in the neighborhood;  
    min  $\leftarrow$  Minimum urgency weight in the neighborhood;  
    urg  $\leftarrow$  Urgency weight of the PDQ q;  
    macPrioLevel :=  $\frac{urg-min}{max-min} * numLevels$ ;  
    return macPrioLevel
```

node of the network, source node of every flow performs the rate control. The function of this rate control policy is to determine at what rate the packets should be injected in the network. As described in section 6.2, the objective of such a flow control is to maximize the utility (or benefit) associated with each flow. Here, whether a packet is injected in a flow or not depends on the utility function of the flow and the size of PDQ at the source node for the flow. Specifically, a flow f injects a packet in the network as long as $U'(x_f) > \beta Q_{d(f)}^{s(f)}(t)$, where $U'(x_f)$ is the first derivative of the utility function U_f . We use $U_f(x_f) = \log(x_f)$ as the utility function as described in [32]. β is a small constant whose value is set to 10^{-6} .

This means that the source node $s(f)$ of a flow f first checks whether $U'(x_f) > \beta Q_{d(f)}^{s(f)}(t)$ condition holds. If the condition holds true, the source node inserts the packet in its PDQ for flow f . On the other hand, if the condition does not hold true, the source node inserts the packets in the source list of the flow. The source list acts as a tentative storage where packets are buffered until rate control permits them to be added in corresponding PDQ. When back-pressure scheduler transmits packets from the PDQ, packets are added in the PDQ from the source list using the rate control condition. At all times, any addition or removal from PDQ is followed by recalculation of urgency weight of the PDQ. If the source node PDQ reflects that

Figure 6.14: Comparison of network throughput, network utility and flow throughput fairness in back-pressure scheduling with and without aggregation (NP-NA - No PDQs, No Aggregation; P-NA - PDQs, No Aggregation; NP-A - No PDQs, Aggregation; P-A - PDQs, Aggregation)

intermediate nodes are sufficiently back-logged, it slows down the rate at which the packets are added from the source list to the PDQ.

6.4.2 Numerical Evaluation

We now present the numerical results obtained using simulation in OPNET [18]. As it is obvious that the above mentioned back-pressure framework requires every node to share their PDQ information with every node in its reach. To implement this, we piggyback the PDQ information on every packet that is exchanged between a node and its neighbors. Specifically, every packet carries an additional UW header which contains the following information: 1) PDQ ID, urgency weight and backlog (in bytes) of the PDQ from which the packet was transmitted, 2) ID and urgency weights of maximum and minimum urgency weight PDQs of the node from which the packet was transmitted. The receiver uses this information from every neighbor to calculate its own UW state. Then the UW state is utilized to calculate the MAC layer priority of an outgoing frame from that node. We use 4 priority levels for MAC transmissions as provided by 802.11e. The aggregation based back-pressure scheduler and rate control were implemented by modifying current 802.11 implementation of OPNET.

We first consider a 50 nodes topology out of which 5 nodes are mesh gateways. All nodes insert 500 Kbps of traffic destined to their nearest gateway. To understand the impact of aggre-

gation, we emulate realistic Internet-type traffic scenario where packet sizes vary substantially [150]. Traffic for every flow is generated randomly in packet sizes of 40, 60, 80, 100, 200, 576 and 1400 bytes with their weights being 40, 15, 10, 5, 5, 5 and 20 percent respectively.

There are various different performance metrics of interest for evaluation of a back-pressure based strategy. We compare our aggregation based scheduling/rate control scheme (P-A - PDQs, Aggregation) to a back-pressure scheduling/rate control scheme which does not perform any aggregation (P-NA - PDQs, No Aggregation). Such a scheme was originally proposed by [32]. Also, for comparison we choose two other schemes where PDQs are not utilized. Depending on whether aggregation is performed or not, these schemes are referred as NP-NA (No PDQs, No Aggregation) and NP-A (No PDQs, Aggregation).

One obvious metric of performance evaluation is aggregate throughput which is simply the sum of throughput of all flows in the network. Two other metrics – network utility and throughput fairness are central to back-pressure based policies. Since the back-pressure framework was originally designed to maximize the network resource utilization while maintaining the fairness among flows, we use both the metrics in our evaluation. Network utility is measured as the sum of logarithm of flow throughput rates ($\sum_{f \in F} \log(x_f)$). For throughput fairness of flows, we use Jain's index [51] which is defines as –

$$\text{Fairness index} = \frac{(\sum_{f=1}^m x_f)^2}{m \sum_{f=1}^m x_f^2} \quad (6.5)$$

where m is total number of flows in the network and x_f is the throughput of every flow.

Fig. 6.14a shows the aggregate throughput achieved with all four schemes. As expected both the schemes with aggregation (P-A and NP-A) achieve relatively higher throughput. Compared to NP-NA scheme, P-NA scheme also provides better throughput. This is due to the fact that spatial bias of nodes closer to gateway is reduced which allows more and more nodes away from gateways to transfer their traffic. It is worth noting that NP-A scheme achieves more throughput compared to P-A scheme but as we will see that the benefits come at the penalty of reduced fairness. The P-A scheme improves the throughput significantly mainly because the backlogged queues are served at faster rates when aggregation is utilized. Without aggregation, every packet of backlogged queues requires additional time for medium access. Also, overhead of MAC layer headers for each frame without aggregation also accounts for a large wastage of bandwidth. Both these issues are well addressed by the utilizing aggregation along with back-pressure policy.

As we described before, the back-pressure strategy was mainly devised to address low network utilization and unfairness issues in multi-hop wireless networks. Even though aggregation with back-pressure scheduling increases the network throughput, it is necessary to verify that it

does not do so by penalizing network utilization or fairness. Fig. 6.14b shows the network utility of back-pressure scheme with and without PDQs and/or aggregation. The NP-NA scheme achieves the highest network utilization because it allows improved throughput while maintaining fairness among the flows. NP-A scheme which achieved highest throughput suffers from lower network utilization due to fairness penalties. The P-A scheme ensures higher service rates of back-logged queues which in turn allows rate control to insert more and more packets in the flow, yielding an improved utilization. Similarly, Fig. 6.14c shows the fairness index calculated for all four schemes. It is observed that plain aggregation (NP-A) does not guarantee higher fairness but when aggregation is directed using back-pressure principles, higher throughput can be achieved without sacrificing fairness.

6.5 Using Back-pressure Principles for Intelligent Channel Width Assignment

We have shown that back-pressure framework can work for alleviate the unfairness among flows in wireless mesh networks. Also, back-pressure policies can be used to direct packet aggregation which also ensures that throughput benefits of aggregation are yielded without sacrificing the fairness. We now show that back-pressure strategy can also be used for intelligent channel width assignment in wireless mesh networks.

With recent advances in Software-defined Radios (SDRs), it has indeed became feasible to dynamically adapt the channel widths at smaller time scales. Even though the advantages of varying channel width (e.g. higher link throughput with higher width) have been explored before, as with most of the physical layer settings (rate, transmission power etc.), naively configuring channel widths of links can in fact have negative impact on wireless network performance. We design a cross-layer channel width assignment scheme that adapts the width according to the backlog of link-layer queues. We leverage the benefits of varying channel widths while adhering to the invariants of back-pressure utility maximization framework. The presented scheme not only guarantees improved throughput and network utilization but also ensures bounded buffer occupancy and fairness.

Even though the advantages of variable channel width assignment have been explored before [49], a few fundamental questions surrounding the problem have largely remained unanswered. Some of the questions are -

1. Do link-level benefits of higher throughput using increased channel width come at other network-wide performance penalties?
2. How can we assign channel width to links such that flows can achieve maximum throughput while maintaining fairness among the flows?

3. Since variable channel width can introduce significant variations among achievable per-link throughput, how can we design a channel width assignment scheme that can guarantee stability of queues and bounded buffer occupancy?

We attempt to answer the questions by utilizing back-pressure principles of utility maximization framework for the purpose of variable channel width assignment. We show that substantial gains in throughput and network utilization can be achieved along with improved fairness when back-pressure framework is used as a directive for channel width assignment. The central idea is to assign higher channel widths to queues with larger backlog (relative to its interference neighborhood).

We briefly revisit the back-pressure framework in order to motivate why and how channel width assignment can be performed using PDQs. Let us assume a network in which transmission time is divided in slots. For a network graph $G = (V, E)$, let $f \in F$ denote a flow from $s(f)$ to $d(f)$. Let $l(u, v) \in E$ denote a link between node u and v , and $\gamma_{l(u,v)}$ be the transmission rate of link $l(u, v)$. Transmission rates of all links in E are presented by $\Gamma = \{\gamma_{l(u,v)}, l(u, v) \in E\}$. Let χ be the set of all possible combinations of rates at which links can operate. Every node $u \in V$ maintains a separate PDQ for destinations of all flows in F . Packets received by u for a flow f destined to $d(f)$ are queued in $Q_u^{d(f)}$. Let $|Q_u^{d(f)}(t)|$ denote the size of the PDQ maintained at node u for destination $d(f)$ at time t . Every node shares its PDQ length information with all its neighbors at the beginning of time slot t . Using this, a node u calculates $D_{l(u,v)}^{d(f)}(t) = |Q_u^{d(f)}(t)| - |Q_v^{d(f)}(t)|$ for all $l(u, v) \in E$ and all $f \in F$. Now, for every link $l(u, v) \in E$, let $\Delta_{l(u,v)}(t) = \max_{f \in F} (D_{l(u,v)}^{d(f)}(t))$. Back-pressure scheduling [149] suggests that Γ at time t should be chosen such that -

$$\Gamma(t) = \max_{\Gamma \in \chi} \sum_{l(u,v) \in E} (\gamma_{l(u,v)} \Delta_{l(u,v)}(t)) \quad (6.6)$$

It can be observed that any approximation of solution to Equ.6.6 should allow PDQs with higher backlog to transmit at a proportionally higher transmission rates. This higher transmission rate can be achieved by assigning the end-points of PDQs (radio interfaces) wider channel widths.

6.5.1 Impact of Varying Channel Width

It is known from Shannon's theorem [139] that for a given transmission scheme (RF parameters and modulation), physical layer transmission rate is proportional to channel width. Increasing channel width not only allows transmitting at higher data rate but the communication range of nodes also decrease. This is especially important because traditionally transmission range and data rate have remain at odds in various problem encountered in literature such as power

control. To further understand this, the relationship between transmission range and channel width can be written as below [48] -

$$\text{Communication Range} = 10^{\frac{P_T - P_{min} - 20 \log_{10}(\frac{4\pi\omega d_0}{c})}{10\eta}} \quad (6.7)$$

where P_T is the transmission power, P_{min} is receiver sensitivity, ω is the channel width in Hz, d_0 is the reference distance, c is the speed of light and η is the path-loss exponent. It can be observed from Equ. 6.7 that increase in the channel width ω results in decrease of the communication range (given that the rest of the parameters are constant).

Another important relationship to understand while studying channel width is that receiver sensitivity also changes with varying channel width. This was first demonstrated in [49, 48]. It was shown that decreasing the channel width by half reduces the receiver sensitivity by 3 dBm. For example, if the receiver sensitivity of a radio is -63 dBm at 80 MHz, reducing the width by half (40 MHz), the receiver sensitivity becomes -66 dBm. This relationship between channel width, receiver sensitivity and communication range is shown in Fig. 6.15 with $\eta = 4$.

6.5.2 Channel Width Assignment using Back-pressure Framework

As discussed before, the central idea behind using back-pressure policies for channel width assignment is twofold. First, since higher channel width can achieve higher transmission rate, PDQs with higher backlog can be assigned higher channel widths to facilitate improved service rate. Second, since the throughput benefits are bounded by PDQ invariants, the fairness and buffer occupancy of flows remain constrained.

Before discussing the algorithm, we outline its scope and relevant assumptions. We use TDMA for scheduling the links. The choice is due to the fact that we are interested in determining the advantages of using back-pressure framework for channel-width assignment while not focusing on designing a distributed protocol that can implement it. For the same reason, we assume that there is no restriction on number of radios available at every node. This allows more than one PDQs to be scheduled on the same node at the same time operating from different radios. We will identify the number of radios necessary in the discrete version of the algorithm later. We now discuss the algorithm for channel width assignment.

Let $P(t)$ be the set of all PDQs in the network at time t . For any PDQ p_i with backlog $b(p_i)$, let $N(p_i)$ be the set of links whose PDQs interfere with the link of p_i . Let $\max(p_i)$ (and $\min(p_i)$) be the backlog of PDQ with maximum (minimum) backlog in $N(p_i)$.

(a) Receiver sensitivity increases with increase in channel width

(b) Communication range decreases quickly with increase in channel width

(c) The relationship between receiver sensitivity and communication range

Figure 6.15: Relationship between channel width, communication range and receiver sensitivity

Algorithm 3 presents two *centralized* and *greedy* schemes of channel width assignment. The first scheme (Algo. 3 - Case 1) targets a *continuous* assignment in which a PDQ can be assigned any width (in Hz) from total spectrum width of D Hz (60 MHz here as in most 802.11 radios). It determines the relative backlog of a PDQ as compared to its neighborhood PDQs in order to proportionally assign a channel width to it. In the case of Algo. 3 - Case 2, only a few pre-selected channel widths can be used by each PDQs. As in 802.11 standards, we choose 4 discrete levels of 5, 10, 20 and 40 MHz.

Algorithm 3 Channel Width Allocation

CASE 1: CONTINUOUS

At the beginning of each time slot t

Sort $P(t)$ in descending order of backlog

for $i = 1 \rightarrow |P(t)|$ **do**

channel width $cw(p_i) = \frac{(b(p_i) - \min(p_i)) \cdot D}{\max(p_i) - \min(p_i)}$

if $cw(p_i)$ width not available in $N(p_i)$ **then**

assign maximum available width in $N(p_i)$ to p_i

end if

end for

CASE 2: DISCRETE

$widthArray[4] = \{5, 10, 20, 40\}$

At the beginning of each time slot t

Sort $P(t)$ in descending order of backlog

for $i = 1 \rightarrow |P(t)|$ **do**

$l = \frac{(b(p_i) - \min(p_i)) \cdot 4}{\max(p_i) - \min(p_i)}$

$cw(p_i) = widthArray[l]$

while $cw(p_i)$ width not available in $N(p_i)$ **do**

$l = l - 1; cw(p_i) = widthArray[l]$

end while

end for

The scheme also reduces the transmission power of radios operating at a lower channel width in such a way that communication range of every node remains constant. Also, note that the number of radios necessary in order for both channel width allocation strategies to work can be very high (e.g. in worst case, D radios of continuous and $D/5$ radios discrete schemes). This along with centralized nature of scheme makes it difficult to implement in practice. Nevertheless, the scheme works well as a proof-of-concept and sets important performance benchmarks for our ongoing distributed protocol design.

Figure 6.16: Average per-flow throughput and network utility increases with varying channel schemes

Figure 6.17: Variable channel width achieves fair resource allocation while ensuring bounded buffer occupancy

6.5.3 Numerical Evaluation

We choose a 7×7 grid with 10 randomly chosen source-destination pairs. Each source node generates 1500 bytes packets using poisson random process with mean of 1350 packets/second. Bi-directional protocol interference model is used for determining the link interference relationships. Also, utility based source node injection rate control [32] is employed. The results of simulation and observations are shown in Figs. 6.16a through 6.17b.

We compare the schemes with two other schemes. First, a *fixed width channel assignment* is used which utilizes back-pressure scheduling but 60 MHz spectrum is divided in 3 channels of 20 MHz fixed widths. Second, a *random scheme* in which the same 3 channels are used but instead of scheduling the links using back-pressure policy, links are randomly chosen for scheduling.

First, we can observe in Fig. 6.16a that average per flow throughput (x_f) increases significantly (by factor of 1.4) when variable channel widths are used. The difference between throughput of fixed channel width and variable channel width is attributed to added spatial reuse that is only available through varying sized channels. The network utility ($\sum_{f \in F} \log(x_f)$) also increases (Fig. 6.16b) with variable channel width. This shows that network resources are better utilized in the case with varying channel width as compared to fixed and random cases.

As we had claimed before, increase of throughput should be fair in order to ensure all flows get equal access of network resources. This is shown in Fig. 6.17a which shows Jain's fairness index for all four schemes. In comparison, varying channel width cases serve the backlogged queues at a faster rate compared to fixed channel width cases. This improves the fairness of starving flows. High fairness of random scheme is due to the fact that random scheme picks every link in an unbiased fashion without any knowledge about its backlog. This results in improved fairness since all links are served at same rate in long period of time. Buffer occupancy is also an important metric of study when back-pressure framework is utilized because it guarantees stability of queues. We can see in Fig. 6.17b that random scheme achieves the worst buffer occupancy because it does not utilize PDQ for link scheduling. All other schemes utilize back-pressure framework which in turn ensure bounded buffer occupancy.

6.6 Concluding Remarks

In this chapter, we showed that back-pressure framework of utility maximization can be used to alleviate inherent spatial bias in resource allocation in wireless mesh networks. We discussed how back-pressure policies can be implemented in a distributed way on CSMA/CA MAC. We then used packet aggregation to improve the efficiency of CSMA implementation of back-pressure framework. At last, we showed that various physical layer resources such channel width can be intelligently assigned using back-pressure invariants and designed a cross-layer variable channel width assignment protocol.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

In this thesis, we investigated various design problems of wireless mesh network with the central focus being their service continuity.

First, we identified various anomalies in throughput capacity behavior when nodes operate at high transmission power levels. In contrast to traditional understanding, we showed that high transmission power level (lower spatial reuse and fewer routing hops) can be beneficial in many representative traffic and topologies.

Second, we addressed the issue of traffic hot-spots in wireless networks by proposing a solution based on centrality power control scheme. Using the centrality heuristic, we showed that if we increase the power levels of only the nodes that are expected to relay more data, significant relay load balancing can be achieved using shortest path routing only.

We then analyzed the service continuity of urban-scale wireless mesh networks by developing two robustness metrics - K-center availability and K-center performability. We developed efficient algorithms for estimating these quantities for large networks. With hundreds of hours of simulation and evaluation based in real-work mesh networks, we derived useful design principles for planning high-availability high-performability mesh networks.

Lastly, we proposed back-pressure framework of network utility maximization as a solution to spatial bias of wireless mesh networks. A packet aggregation scheme was developed that can increase the efficiency of back-pressure policy implementation on CSMA/CA. At the end, we developed a cross-layer channel width assignment protocol which showed that many cross-layer design protocols can be built in similar manner using back-pressure framework.

7.2 Future Work

We believe that the concepts of KCA and KCP can be useful to network designers to plan and deploy networks, as can the evaluation methods we have described for them. Increasing the number of deployed nodes can result into unnecessary expenditure while increasing transmission power level might have performance related penalties. If a higher value of KCA is necessary (network must be highly available) while not guaranteeing any specific KCP, deploying the minimum number of nodes necessary for coverage, and utilizing high transmission power, can be a significantly more cost effective solution. Designing a network with a target KCA and KCP while meeting the coverage requirement is a challenging optimization problem. For future work, we want to design networks that can guarantee a specific KCA and KCP. Various potential design problems emerging from this are discussed below.

7.2.1 Designing for Availability and Performability

So far we have discussed how to provide mesh network designers the tools which can help them in understanding the KCA and KCP of mesh networks. We now discuss how specific constrained design optimization tools can be built using the evaluation tools.

Network Deployment

Designing and deploying a mesh network with high KCA and KCP requires that link failures such as shadowing failures are taken into consideration from the planning phase. A typical network design and deployment problem requires a network to be deployed in the given geographical area such that necessary coverage is obtained. In any such problem, the following are usually available to network designers.

Potential locations. In the geographical area where network has to be deployed, potential locations are the locations where it is possible to place a mesh node. These locations are typically constrained by availability of buildings, street light poles, and other facilities in the neighborhood. This also includes a subset of locations for gateway nodes where wired connections (typically to the Internet) are feasible.

Environment R/F profile (RFP). It includes the wireless propagation characteristics of the outdoor environment where the network is being deployed. Using state-of-the-art measurement methods and site surveys, parameters such as signal path loss and shadowing coefficient can be determined. As we saw before, these are especially important in derivation of edge failure probabilities due to shadowing failures.

Mesh node profile (MNP). This is a set of parameters related to the radios used in mesh nodes. This includes information such as the level of noise, maximum transmit power level,

receiver sensitivities and their corresponding data rates. In a two-tier mesh architecture, this information must be available for both backhaul and access tier radios. Also, MNP includes the information about the gain of the antenna (assumed to be omni-directional) used with backhaul tier radio. This together with maximum transmit power determines the effective transmit power of the radio.

Coverage constraint. The fundamental requirement of deploying a mesh network is to provide coverage of necessary locations. Hence, it is a common constraint to all our optimization problems. An accurate and practical way of finding the coverage requirements is to acquire all the locations where there is going to be some expected traffic demand. All such locations are then listed as a set of location which have to be covered by at least one mesh node. Since the access tier links (links between the clients and mesh nodes) are also prone to shadowing failures, the probability that received signal strength at a location from a mesh node is higher than the access tier receiver sensitivity threshold is also the probability that the location is covered by that mesh node. Let C be the set of all coverage locations. Now, the coverage requirement is described as follows. For all locations $c_i \in C$, the probability that c_i is covered by a mesh nodes should be at least θ_{c_i} and c_i should be covered by at least M_{c_i} mesh nodes. This representation allows consideration of locations which should be covered by multiple mesh nodes, because high traffic demand is expected at those locations.

Given this input information and constraint, a designer can intelligently choose the locations where mesh nodes should be deployed, and their transmit power levels, such that a target level of KCA and KCP is achieved, or KCA and KCP of the network is maximized. Here, the design and deployment involves determination of topological factors; especially node density, node positions and transmit power levels. Because there is a complex interplay between these topological factors and how they impact the KCA and KCP of the network, there are numerous flavors of the general design and deployment optimization problem. Below we articulate some of these problems and discuss how they can be useful.

- **Design problem 1.** Given potential locations, MNP, RFP, a set of mesh nodes and their transmit power levels, determine a node placement such that KCA and KCP are maximized while meeting the coverage constraint.
- **Design problem 2.** Given potential locations, MNP, RFP and a set of mesh nodes, determine a node placement and transmit power levels of mesh nodes such that KCA and KCP are maximized, and coverage constraint is met.
- **Design problem 3.** Given potential locations, MNP and RFP, determine a node placement and transmit power levels of mesh nodes such that the number of required mesh nodes are minimized, coverage constraint is met, and targeted KCA and KCP is achieved.

It is assumed in all the three problems that link failure probabilities are either available or derived using the shadowing failure model. Also, once a candidate node placement is found, its gateway placement is also necessary to calculate KCA and KCP. This problem of gateway assignment is well-studied; one of the current, more sophisticated methods is presented by [134]. This method assigns gateways to graph centers based on collision load balancing. In case of problem 1 and 2, if the given number of nodes can not satisfy the coverage, the conclusion is that there does not exist a valid and feasible node placement.

If we also assume that transmit power level of access tier radios are uniform for all mesh nodes (a reasonable practical case, even though this is not a requirement in any of the above mentioned design problems), it allows the following discussion with brevity.

In an optimal solution to Problem 1, nodes should be placed such that there is high link redundancy among the backhaul links and the lowest possible collisions around the gateways. The former guarantees higher KCA and latter provides a high value of KCP. With all possible locations and given mesh node power levels, there can be a large number of combinations where the coverage requirement is satisfied. Choosing a placement from all possible combinations which optimized the KCA and KCP can be a difficult problem. As a greedy heuristic solution to the problem, nodes can be placed in a square grid on the network area such that nodes with lower power levels are placed on grid locations nearer to high density coverage areas and nodes with higher power levels are placed on grid locations around low density coverage areas. The grid can then be perturbed such that nodes move towards their nearest coverage regions, allowing low power nodes to move more as compared to high power nodes. This results into areas where high coverage is available with lower collisions (higher KCP) while having sufficient redundancy in high power backhaul links (higher KCA). Of course, such greedy heuristics can result into unpredictable performance, but point the road to more sophisticated heuristics.

Similarly, if we assume that in Problem 2 the coverage locations are uniformly distributed in the network area, the solution to the problem of maximizing only the KCA might be trivial. This is because placing the nodes as uniformly as possible (e.g. a square grid) and assigning them the maximum possible transmit power levels will always result in the highest KCA. However, the problem is less trivial in the case where coverage locations are not uniformly distributed in the network area. Further, when it is essential to maximize KCP along with KCA, increasing power levels to the maximum possible level might not yield a solution, since increased power levels can cause high interference and degraded performance. The difference between Problem 1 and Problem 2 is that Problem 2 allows the choice of power levels along with the node placement. If we know the optimal solution to Problem 1, we can restate Problem 2 with an additional requirement that all the nodes should operate at the same power level. Once a candidate node placement is achieved, the power levels of nodes can be then modified to improve the KCP while maintaining the same KCA. Since this method of solving Problem 2 does not yield an

optimal solution, this problem, too, remains open for more innovative solutions.

Problem 3 is different from the other two in that the objective is now to minimize the total number of required mesh nodes while meeting KCA, KCP and coverage constraints. This is especially an interesting problem from the designer's perspective, since it tries to minimize the cost associated with required number of mesh nodes in a greenfield deployment. As opposed to unrestricted coverage problems studied extensively in sensor networks, here the solution to the optimization problem guarantees target reliability and performability while minimizing the total cost. Methods such as restricted Steiner trees, where Steiner points are the mesh nodes and coverage locations are the leaf nodes, yield very poor solution since most such approaches try to minimize the number of backhaul link connections. This results in a sparse backhaul and a lower value of KCA and KCP. In Problem 3, it might be possible that even with a large number of nodes it is not possible to achieve a certain target KCP due to the inherent trade-off between the lower resilience of sparser topologies, and the lower throughput of denser topologies. In such a case, a solution to Problem 2 can yield the maximum possible value of KCA and KCP. When a designer can choose the node positions and transmit power levels for a new deployment, a solution to Problem 3 can indeed be very crucial in guaranteeing reliable performance.

Network Re-formation

The GoogleWiFi example motivates the consideration that if the network is already deployed, it may be possible to reform the network topology to achieve higher KCA and KCP. The design problems 1, 2 and 3 pertain mainly to greenfield deployments but related optimization problems can be defined for networks which are already deployed. For an existing mesh network, k -center availability and performability can be evaluated. If the network falls short in providing a reliable performance, it may be possible to refine its design (to some extent) to improve its KCA and KCP. We refer to this as the network re-formation problem.

Three ways of performing network reformation can be identified: adding additional mesh nodes, readjusting transmit power level of nodes, and repositioning the mesh nodes. Based on the network's current availability and performability, one or more out of these three options should be considered in re-formation.

Note that many of such network re-formation problems can be mapped back to problems of new network deployment with some modifications. As an example, the problem of repositioning of the mesh nodes is equivalent to design problem 1. The other two network reformation problems can be stated as below.

- **Design problem 4.** Given potential locations, MNP, RFP, node positions and power levels of currently deployed mesh nodes, determine the node placement and transmit

power levels of additional mesh nodes such that number of required additional mesh nodes is minimized, and targeted KCA and KCP is achieved.

- **Design problem 5.** Given MNP, RFP and node positions of currently deployed mesh nodes, determine the power levels of mesh nodes such that KCA and KCP are maximized.

Note that the difference between Problem 4 and Problem 3 is that Problem 4 pertains to the case where some of the mesh nodes are already deployed. We do not include the coverage constraint in both of these subproblems since an existing mesh network must already meet the coverage requirement and the re-formation is only necessary for improved KCA and KCP. If readjusting the power levels of mesh nodes (solution of Problem 5) attains a desired level KCA and KCP, additional nodes (Problem 4) might not be necessary in reformation. Since power control is clearly an inexpensive option for network reformation, solution to Problem 5 might be especially valuable. There can be similar other versions of design optimization problems in network reformation domain.

REFERENCES

- [1] Aruba Networks - Mesh Solution. <http://www.arubanetworks.com>.
- [2] Ath5k and Ath9k. <http://madwifi-project.org>.
- [3] Broadband Wireless Network Lab - Mesh Testbed. <http://www.ece.gatech.edu/research/labs/bwn/mesh/testbed.html>.
- [4] CentMesh Outdoor Wireless Testbed. <http://centmesh.csc.ncsu.edu>.
- [5] Chipcon CC2420. <http://www.ti.com>.
- [6] Cisco Systems. <http://www.cisco.com/en/US/netsol/ns621/index.html>.
- [7] CUWIN Community Wireless Network. <http://cuwireless.net>.
- [8] EmuLab. <http://www.emulab.net/>.
- [9] Google WiFi, Mountain View, California. <http://wifi.google.com/>.
- [10] Load balancing in dense wireless multihop networks. <http://userver.ftw.at/~esa/java/multihop/>.
- [11] MadWifi. <http://madwifi-project.org/>.
- [12] Meraki Inc. <http://www.meraki.com>.
- [13] MeshNet Project. <http://moment.cs.ucsb.edu/meshnet/>.
- [14] Micaz mote module. <http://www.xbow.com>.
- [15] Microsoft Connectivity Layer. <http://research.microsoft.com/en-us/projects/mesh/>.
- [16] MIT Roofnet Project. <http://pdos.csail.mit.edu/roofnet/doku.php>.
- [17] Network simulator, version - 3. <http://www.nsnam.org>.
- [18] OPNET Network Simulator. <http://www.opnet.com>.
- [19] ORBIT Lab - WINLAB Rutgers University. <http://www.orbit-lab.org/>.
- [20] Ponca city wireless network. <http://www.myponcacity.com/wifi/poncaradios.html>.
- [21] Purdue Mesh Network. <https://engineering.purdue.edu/MESH>.
- [22] Ruckus Wireless. <http://www.ruckuswireless.com/>.
- [23] Soekris Engineering. <http://www.soekris.com>.
- [24] SolarMESH Project. <http://owl.mcmaster.ca/~todd/SolarMESH>.

- [25] Tropos Networks. <http://www.tropos.com>.
- [26] VIA Technologies Inc. <http://www.via.com.tw>.
- [27] WiMax. <http://www.wimaxforum.org/>.
- [28] WiseNet Testbed. <http://research.csc.ncsu.edu/netsrv/?q=node/6>.
- [29] Five keys to successful metro-scale wi-fi deployment. *Tropos Networks White Paper*, December 2004.
- [30] Aditya Akella, Glenn Judd, Srinivasan Seshan, and Peter Steenkiste. Self-management in chaotic wireless deployments. *Wirel. Netw.*, 13(6):737–755, 2007.
- [31] Ian F. Akyildiz, Xudong Wang, and Weilin Wang. Wireless mesh networks: a survey. *Comput. Netw. ISDN Syst.*, 47(4):445–487, 2005.
- [32] U. Akyol, M. Andrews, P. Gupta, J. Hobby, I. Saniee, and A. Stolyar. Joint scheduling and congestion control in mobile ad-hoc networks. In *INFOCOM 2008. The 27th Conference on Computer Communications. IEEE*, pages 619 –627, april 2008.
- [33] Yair Amir, Claudiu Danilov, Michael Hilsdale, Raluca Musăloiu-Elefteri, and Nilo Rivera. Fast handoff for seamless wireless mesh networks. In *MobiSys '06: Proceedings of the 4th international conference on Mobile systems, applications and services*, pages 83–95, New York, NY, USA, 2006. ACM.
- [34] A. Annamalai, C. Tellambura, and V.K. Bhargava. Simple and accurate methods for outage analysis in cellular mobile radio systems-a unified approach. *Communications, IEEE Transactions on*, 49, 2001.
- [35] P. Antoniadis, B. Le Grand, A. Satsiou, L. Tassiulas, R.L. Aguiar, J.P. Barraca, and S. Sargento. Community building over neighborhood wireless mesh networks. *Technology and Society Magazine, IEEE*, 27(1):48–56, Spring 2008.
- [36] Baruch Awerbuch and David Peleg. Online tracking of mobile users. *J. ACM*, 42:1021–1058, September 1995.
- [37] H. Balakrishnan and V.N. Padmanabhan. How network asymmetry affects tcp. *Communications Magazine, IEEE*, 39(4):60 –67, apr 2001.
- [38] A. Bar-Noy and I. Kessler. Tracking mobile users in wireless communications networks. *Information Theory, IEEE Transactions on*, 39(6):1877 –1886, nov 1993.
- [39] Giacomo Bernardi, Peter Buneman, and Mahesh K. Marina. Tegola tiered mesh network testbed in rural scotland. In *WiNS-DR '08: Proceedings of the 2008 ACM workshop on Wireless networks and systems for developing regions*, pages 9–16, New York, NY, USA, 2008. ACM.
- [40] Christian Bettstetter and Christian Hartmann. Connectivity of wireless multihop networks in a shadow fading environment. *Wirel. Netw.*, 11(5):571–579, September 2005.

- [41] Sanjit Biswas and Robert Morris. ExOR: opportunistic multi-hop routing for wireless networks. *SIGCOMM Comput. Commun. Rev.*, 35(4):133–144, 2005.
- [42] Douglas M. Blough and Paolo Santi. Investigating upper bounds on network lifetime extension for cell-based energy conservation techniques in stationary ad hoc networks. In *Proceedings of the 8th annual international conference on Mobile computing and networking*, MobiCom '02, pages 183–192, New York, NY, USA, 2002. ACM.
- [43] Ulrik Brandes. A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology*, 25:163–177, 2001.
- [44] Ulrik Brandes and Thomas Erlebach. *Network Analysis: Methodological Foundations*. Springer-Verlag Berlin Heidelberg, 2005.
- [45] Gurashish Brar, Douglas M. Blough, and Paolo Santi. Computationally efficient scheduling with the physical interference model for throughput improvement in wireless mesh networks. In *MobiCom '06: Proceedings of the 12th annual international conference on Mobile computing and networking*, pages 2–13, New York, NY, USA, 2006. ACM.
- [46] Martin Burkhart, Pascal von Rickenbach, Roger Wattenhofer, and Aaron Zollinger. Does topology control reduce interference? In *MobiHoc '04: Proceedings of the 5th ACM international symposium on Mobile ad hoc networking and computing*, pages 9–19, New York, NY, USA, 2004. ACM.
- [47] Joseph Camp, Joshua Robinson, Christopher Steger, and Edward Knightly. Measurement driven deployment of a two-tier urban mesh access network. In *MobiSys '06: Proceedings of the 4th international conference on Mobile systems, applications and services*, pages 96–109, New York, NY, USA, 2006. ACM.
- [48] Celso Barbosa Carvalho and Jose Ferreira de Rezende. Routing in ieee 802.11 wireless mesh networks with channel width adaptation. In *Ad Hoc Networking Workshop (Med-Hoc-Net), 2010 The 9th IFIP Annual Mediterranean*, pages 1–8, june 2010.
- [49] Ranveer Chandra, Ratul Mahajan, Thomas Moscibroda, Ramya Raghavendra, and Paramvir Bahl. A case for adapting channel width in wireless networks. In *Proceedings of the ACM SIGCOMM 2008 conference on Data communication*, SIGCOMM '08, pages 135–146, New York, NY, USA, 2008. ACM.
- [50] L. Chen, S. H. Low, M. Chiang, and J. C. Doyle. Cross-layer congestion control, routing and scheduling design in ad hoc wireless networks. In *INFOCOM 2006. 25th IEEE International Conference on Computer Communications. Proceedings*, pages 1–13, 2006.
- [51] Dah-Ming Chiu and Raj Jain. Analysis of the increase and decrease algorithms for congestion avoidance in computer networks. *Computer Networks and ISDN Systems*, 17(1):1–14, 1989.
- [52] Charles J. Colbourn. *The Combinatorics of Network Reliability*. Oxford University Press, Inc., New York, NY, USA, 1987.

- [53] Murat Demirbas, Anish Arora, and Mohamed G. Gouda. A pursuer-evader game for sensor networks. In *Proceedings of the 6th international conference on Self-stabilizing systems*, SSS'03, pages 1–16, Berlin, Heidelberg, 2003. Springer-Verlag.
- [54] Gaurish Deuskar, Parth H. Pathak, and Rudra Dutta. Packet aggregation based back-pressure scheduling in multi-hop wireless networks. In *Wireless Communications and Networking Conference (WCNC), 2012 IEEE*, pages 1263–1268, april 2012.
- [55] Richard Draves, Jitendra Padhye, and Brian Zill. Routing in multi-radio, multi-hop wireless mesh networks. In *MobiCom '04: Proceedings of the 10th annual international conference on Mobile computing and networking*, pages 114–128, New York, NY, USA, 2004. ACM.
- [56] E. C. Efstathiou, P. A. Frangoudis, and G. C. Polyzos. Stimulating participation in wireless community networks. In *INFOCOM 2006. 25th IEEE International Conference on Computer Communications. Proceedings*, pages 1–13, April 2006.
- [57] G. Egeland and P. Engelstad. The availability and reliability of wireless multi-hop networks with stochastic link failures. *Selected Areas in Communications, IEEE Journal on*, 27(7), 2009.
- [58] S.M. ElRakabawy, S. Frohn, and C. Lindemann. Scalemesh: A scalable dual-radio wireless mesh testbed. *Sensor, Mesh and Ad Hoc Communications and Networks Workshops, 2008. SECON Workshops '08. 5th IEEE Annual Communications Society Conference on*, pages 1–6, June 2008.
- [59] A. Eryilmaz and R. Srikant. Joint congestion control, routing, and mac for stability and fairness in wireless networks. *Selected Areas in Communications, IEEE Journal on*, 24(8):1514–1524, 2006.
- [60] A. Eshete, A. Arcia, D. Ros, and Yuming Jiang. Impact of wimax network asymmetry on tcp. In *Wireless Communications and Networking Conference, 2009. WCNC 2009. IEEE*, pages 1–6, april 2009.
- [61] George S. Fishman. A monte carlo sampling plan for estimating network reliability. *Operations Research*, 34(4):pp. 581–594, 1986.
- [62] L. C Freeman. A set of measuring centrality based on betweenness. In *Sociometry*, volume 40, pages 35–41, 1977.
- [63] Jason A. Fuemmeler, Nitin H. Vaidya, and Venugopal V. Veeravalli. Selecting transmit powers and carrier sense thresholds in CSMA protocols for wireless ad hoc networks. In *WICON '06: Proceedings of the 2nd annual international workshop on Wireless internet*, page 15, New York, NY, USA, 2006. ACM.
- [64] S. Ganguly, V. Navda, Kyungtae Kim, A. Kashyap, D. Niculescu, R. Izmailov, Sangjin Hong, and S.R. Das. Performance optimizations for deploying voip services in mesh networks. *Selected Areas in Communications, IEEE Journal on*, 24(11):2147–2158, nov. 2006.

- [65] Jie Gao and Li Zhang. Trade-offs between stretch factor and load-balancing ratio in routing on growth-restricted graphs. *Parallel and Distributed Systems, IEEE Transactions on*, 20(2):171–179, 2009.
- [66] Michele Garetto, Theodoros Salonidis, and Edward W. Knightly. Modeling per-flow throughput and capturing starvation in csma multi-hop wireless networks. *IEEE/ACM Trans. Netw.*, 16(4):864–877, August 2008.
- [67] Michele Garetto, Jingpu Shi, and Edward W. Knightly. Modeling media access in embedded two-flow topologies of multi-hop wireless networks. In *Proceedings of the 11th annual international conference on Mobile computing and networking*, MobiCom '05, pages 200–214, New York, NY, USA, 2005. ACM.
- [68] M. Gastpar and M. Vetterli. On the capacity of wireless networks: the relay case. *INFOCOM 2002. Twenty-First Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE*, 3:1577–1586 vol.3, 2002.
- [69] Michael J. Neely Georgiadis Leonidas and Leandros Tassiulas. Resource allocation and cross-layer control in wireless networks. In *Foundations and Trends in Networking*, 2006.
- [70] T.M.S. Gomes and J.M.F. Craveirinha. Algorithm for sequential generation of states in failure-prone communication network. *Communications, IEE Proceedings-*, 145(2):73–79, apr 1998.
- [71] J. Gomez and A.T. Campbell. A case for variable-range transmission power control in wireless multihop networks. *INFOCOM 2004. Twenty-third Annual Joint Conference of the IEEE Computer and Communications Societies*, 2:1425–1436 vol.2, March 2004.
- [72] Olga Goussevskaya, Yvonne Anne Oswald, and Roger Wattenhofer. Complexity in geometric SINR. In *MobiHoc '07*. ACM.
- [73] B. Greenstein, D. Estrin, R. Govindan, S. Ratnasamy, and S. Shenker. Difs: a distributed index for features in sensor networks. In *Sensor Network Protocols and Applications, 2003. Proceedings of the First IEEE. 2003 IEEE International Workshop on*, pages 163–173, may 2003.
- [74] P. Gupta and P.R. Kumar. The capacity of wireless networks. *Information Theory, IEEE Transactions on*, 46(2):388–404, Mar 2000.
- [75] D.D. Harms. *Network reliability: experiments with a symbolic algebra environment*. CRC Press, 1995.
- [76] B.R. Haverkort, R. Marie, G. Rubino, and Trivedi K. *Performability modelling: techniques and tools*. Wiley, 2001.
- [77] Van Mieghem Hekmat R. Connectivity in wireless ad-hoc networks with log-normal radio model. *Mobile Networks and Applications*, 2006.
- [78] Janine Illian, Antti Penttinen, Helga Stoyan, and Dietrich Stoyan. *Statistical Analysis and Modelling of Spatial Point Patterns*. Wiley-Interscience Ltd., 2008.

- [79] Ashish Jain, Marco Gruteser, Mike Neufeld, and Dirk Grunwald. Benefits of packet aggregation in ad-hoc wireless network. Technical report, 2003.
- [80] Kamal Jain, Jitendra Padhye, Venkata N. Padmanabhan, and Lili Qiu. Impact of interference on multi-hop wireless network performance. In *MobiCom '03: Proceedings of the 9th annual international conference on Mobile computing and networking*, pages 66–80, New York, NY, USA, 2003. ACM.
- [81] Douglas R. Shier James Jarvis. An improved algorithm for approximating the performance of stochastic flow networks. *Inform. jour. on comp.*, '96.
- [82] Xiaohua Jia, Dongsoo Kim, S. Makki, Peng-Jun Wan, and Chih-Wei Yi. Power assignment for k-connectivity in wireless ad hoc networks. *INFOCOM 2005. 24th Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings IEEE*, 3:2206–2211 vol. 3, March 2005.
- [83] Jangeun Jun and M.L. Sichitiu. The nominal capacity of wireless mesh networks. *Wireless Communications, IEEE*, 10(5):8–14, Oct 2003.
- [84] V. Kawadia and P.R. Kumar. Principles and protocols for power control in wireless ad hoc networks. *Selected Areas in Communications, IEEE Journal on*, 23(1):76–88, Jan. 2005.
- [85] J. Mark Keil and Carl A. Gutwin. The delauney triangulation closely approximates the complete euclidean graph. In *WADS '89: Proceedings of the Workshop on Algorithms and Data Structures*, pages 47–56, London, UK, 1989. Springer-Verlag.
- [86] F. Kelly, A. Maulloo, and D. Tan. Rate control in communication networks: shadow prices, proportional fairness and stability. In *Journal of the Operational Research Society*, volume 49, 1998.
- [87] R. Khalaf and I. Rubin. Enhancing the throughput-delay performance of ieee802.11 based networks through direct transmissions. *VTC 2004*.
- [88] Tae-Suk Kim, Hyuk Lim, and Jennifer C. Hou. Improving spatial reuse through tuning transmit power, carrier sense threshold, and data rate in multihop wireless networks. In *MobiCom '06: Proceedings of the 12th annual international conference on Mobile computing and networking*, pages 366–377, New York, NY, USA, 2006. ACM.
- [89] Dzmitry Kliazovich and Fabrizio Granelli. Packet concatenation at the ip level for performance enhancement in wireless local area networks. *Wirel. Netw.*, 14(4):519–529, 2008.
- [90] Sungoh Kwon and N.B. Shroff. Paradox of shortest path routing for large multi-hop wireless networks. *INFOCOM 2007. 26th IEEE International Conference on Computer Communications. IEEE*, pages 1001–1009, May 2007.
- [91] P. Kyasanur, Jungmin So, C. Chereddi, and N.H. Vaidya. Multichannel mesh networks: challenges and protocols. *Wireless Communications, IEEE*, 13(2):30–36, April 2006.

- [92] Pradeep Kyasanur and Nitin H. Vaidya. Capacity of multi-channel wireless networks: impact of number of channels and interfaces. In *MobiCom '05: Proceedings of the 11th annual international conference on Mobile computing and networking*, pages 43–57, New York, NY, USA, 2005. ACM.
- [93] Kun-chan Lan, Zhe Wang, Mahbub Hassan, Tim Moors, Rodney Berriman, Lavy Libman, Maximilian Ott, Bjorn Landfeldt, and Zainab Zaidi. Experiences in deploying a wireless mesh network testbed for traffic control. *SIGCOMM Comput. Commun. Rev.*, 37(5):17–28, 2007.
- [94] Pasi Lassila. Spatial node distribution of the random waypoint mobility model with applications. *IEEE Transactions on Mobile Computing*, 5(6):680–694, 2006. Member-Hyytia, Esa and Member-Virtamo, Jorma.
- [95] Fan Li and Yu Wang. Circular sailing routing for wireless networks. *INFOCOM 2008. The 27th Conference on Computer Communications. IEEE*, pages 1346–1354, April 2008.
- [96] Fan Li and Yu Wang. Stretch factor of curveball routing in wireless network: Cost of load balancing. In *Communications, 2008. ICC '08. IEEE International Conference on*, pages 2650–2654, May 2008.
- [97] N. Li, J.C. Hou, and L. Sha. Design and analysis of an mst-based topology control algorithm. *INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications Societies. IEEE*, 3:1702–1712 vol.3, March-3 April 2003.
- [98] Xin Li, Young Jin Kim, Ramesh Govindan, and Wei Hong. Multi-dimensional range queries in sensor networks. In *Proceedings of the 1st international conference on Embedded networked sensor systems*, SenSys '03, pages 63–75, New York, NY, USA, 2003. ACM.
- [99] Xiaojun Lin and N.B. Shroff. Joint rate control and scheduling in multihop wireless networks. In *Decision and Control, 2004. CDC. 43rd IEEE Conference on*, volume 2, pages 1484 – 1489 Vol.2, 2004.
- [100] Christian Lochert, Björn Scheuermann, and Martin Mauve. A survey on congestion control for mobile ad hoc networks: Research articles. *Wirel. Commun. Mob. Comput.*, 7(5):655–676, June 2007.
- [101] Mihail L.Sichitiu and Rudra Dutta. Benefits of multiple battery levels for the lifetime of large wireless sensor networks. In *NETWORKING 2005*, volume 3462 of *Lecture Notes in Computer Science*, pages 403–408. Springer Berlin / Heidelberg, 2005.
- [102] M. Mallinson, P. Drane, and S. Hussain. Discrete radio power level consumption model in wireless sensor networks. In *Mobile Adhoc and Sensor Systems, 2007. MASS 2007. IEEE International Conference on*, pages 1 –6, October 2007.
- [103] Vincenzo Mancuso, Omer Gurewitz, Ahmed Khattab, and Edward W. Knightly. Elastic rate limiting for spatially biased wireless mesh networks. In *Proceedings of the 29th conference on Information communications*, INFOCOM'10, pages 1720–1728, Piscataway, NJ, USA, 2010. IEEE Press.

- [104] E. Manzi, M. Labbe, and F. Maffioli Latouche, G. Fishman's sampling plan for computing network reliability. *Reliability, IEEE Trans. on*, 2001.
- [105] A. Mei and J. Stefa. Routing in outer space. *INFOCOM 2008. The 27th Conference on Computer Communications. IEEE*, pages 2234–2242, April 2008.
- [106] Alessandro Mei and Julinda Stefa. Routing in outer space: fair traffic load in multi-hop wireless networks. In *MobiHoc '08*, pages 23–32, 2008.
- [107] Jeffrey P. Monks, Vaduvur Bharghavan, and Wen mei W. Hwu. A power controlled multiple access protocol for wireless packet networks. In *INFOCOM 2001. 20th Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings IEEE*, pages 219–228, 2001.
- [108] A. Muqattash and M. Krunz. Power controlled dual channel (PCDC) medium access protocol for wireless ad hoc networks. *INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications Societies. IEEE*, 1:470–480 vol.1, March-3 April 2003.
- [109] A. Muqattash and M. Krunz. POWMAC: a single-channel power-control protocol for throughput enhancement in wireless ad hoc networks. *Selected Areas in Communications, IEEE Journal on*, 23(5):1067–1084, May 2005.
- [110] C. Na, J.K. Chen, and T.S. Rappaport. Measured traffic statistics and throughput of ieee 802.11b public wlan hotspots with three different applications. *Wireless Communications, IEEE Transactions on*, 5(11):3296 –3305, november 2006.
- [111] Swetha Narayanaswamy, Vikas Kawadia, R. S. Sreenivas, and P. R. Kumar. The COM-POW protocol for power control in ad hoc networks: Theory, architecture, algorithm, implementation, and experimentation. *European Wireless Conference*, 2002.
- [112] M.J. Neely, E. Modiano, and Chih-Ping Li. Fairness and optimal stochastic control for heterogeneous networks. In *INFOCOM 2005. 24th Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings IEEE*, volume 3, pages 1723 – 1734 vol. 3, 2005.
- [113] Mark E. J. Newman, D. J. Watts, and S. H. Strogatz. Random graph models of social networks. volume 99, pages 2566–2572, 2002.
- [114] Erik Nordström, Per Gunningberg, Christian Rohner, and Oskar Wibling. Evaluating wireless multi-hop networks using a combination of simulation, emulation, and real world experiments. In *MobiEval '07: Proceedings of the 1st international workshop on System evaluation for mobile platforms*, pages 29–34, New York, NY, USA, 2007. ACM.
- [115] Parth H. Pathak and Rudra Dutta. Impact of power control on capacity of large scale wireless mesh networks. In *Third IEEE International Conference on Advanced Networks and Telecommunication Systems (ANTS)*, New Delhi, India, 12 2009.

- [116] Parth H. Pathak and Rudra Dutta. Impact of power control on relay load balancing in wireless sensor networks. In *Wireless Communications and Networking Conference (WCNC), 2010 IEEE*, pages 1–6, april 2010.
- [117] Parth H. Pathak and Rudra Dutta. Centrality-based power control for hot-spot mitigation in multi-hop wireless networks. *Computer Communications*, 35(9):1074 – 1085, 2012. Special Issue: Wireless Sensor and Robot Networks: Algorithms and Experiments.
- [118] Parth H. Pathak, Divya Gupta, and Rudra Dutta. Loner links aware routing and scheduling wireless mesh networks. *ANTS 2008. 2nd Advanced Networking and Telecommunications System Conference. IEEE*, December 2008.
- [119] Parth H. Pathak, Sankalp Nimbhorkar, and Rudra Dutta. Channel width assignment using relative backlog: extending back-pressure to physical layer. In *Proceedings of the thirteenth ACM international symposium on Mobile Ad Hoc Networking and Computing, MobiHoc '12*, pages 249–250, New York, NY, USA, 2012. ACM.
- [120] P.H. Pathak and R. Dutta. Using centrality-based power control for hot-spot mitigation in wireless networks. In *Global Telecommunications Conference (GLOBECOM 2010), 2010 IEEE*, pages 1–6, dec. 2010.
- [121] P.H. Pathak and R. Dutta. Impact of power control on capacity of tdm-scheduled wireless mesh networks. In *Communications (ICC), 2011 IEEE International Conference on*, pages 1–6, june 2011.
- [122] P.H. Pathak and R. Dutta. A survey of network design problems and joint design approaches in wireless mesh networks. *Communications Surveys Tutorials, IEEE*, 13(3):396–428, quarter 2011.
- [123] M. D. Penrose. The longest edge of the random minimal spanning tree. *The Annals of Applied Probability*, 7(2):340–361, 1997.
- [124] E. Pitoura and G. Samaras. Locating objects in mobile computing. *Knowledge and Data Engineering, IEEE Transactions on*, 13(4):571–592, jul/aug 2001.
- [125] Lucian Popa, Afshin Rostamizadeh, Richard Karp, Christos Papadimitriou, and Ion Stoica. Balancing traffic load in wireless networks with curveball routing. In *MobiHoc '07: Proceedings of the 8th ACM international symposium on Mobile ad hoc networking and computing*, pages 170–179, New York, NY, USA, 2007. ACM.
- [126] A. Prasad Sistla, O. Wolfson, S. Chamberlain, and S. Dao. Modeling and querying moving objects. In *Data Engineering, 1997. Proceedings. 13th International Conference on*, pages 422–432, apr 1997.
- [127] Lili Qiu, Yin Zhang, Feng Wang, Mi Kyung Han, and Ratul Mahajan. A general model of wireless interference. In *Proceedings of the 13th annual ACM international conference on Mobile computing and networking, MobiCom '07*, pages 171–182, New York, NY, USA, 2007. ACM.

- [128] R. Raghavendra, A.P. Jardosh, E.M. Belding, and Haitao Zheng. Ipac: Ip-based adaptive packet concatenation for multihop wireless networks. pages 2147–2153, 29 2006-nov. 1 2006.
- [129] K. N. Ramachandran, E. M. Belding, K. C. Almeroth, and M. M. Buddhikot. Interference-aware channel assignment in multi-radio wireless mesh networks. *INFOCOM 2006. 25th IEEE International Conference on Computer Communications. Proceedings*, pages 1–12, April 2006.
- [130] Theodore Rappaport. *Wireless Communications: Principles and Practice*. Prentice Hall PTR, Upper Saddle River, NJ, USA, 2nd edition, 2001.
- [131] Charles Reis, Ratul Mahajan, Maya Rodrig, David Wetherall, and John Zahorjan. Measurement-based models of delivery and interference in static wireless networks. In *SIGCOMM '06: Proceedings of the 2006 conference on Applications, technologies, architectures, and protocols for computer communications*, pages 51–62, New York, NY, USA, 2006. ACM.
- [132] R. Riggio, D. Miorandi, F. De Pellegrini, F. Granelli, and I. Chlamtac. A traffic aggregation and differentiation scheme for enhanced qos in ieee 802.11-based wireless mesh networks. *Comput. Commun.*, 31(7):1290–1300, 2008.
- [133] J. Robinson and E.W. Knightly. A performance study of deployment factors in wireless mesh networks. *INFOCOM 2007. 26th IEEE International Conference on Computer Communications. IEEE*, pages 2054–2062, May 2007.
- [134] J. Robinson, M. Uysal, R Swami, and E. Knightly. Adding capacity points to a wireless mesh network using local search. In *IEEE INFOCOM 2008*.
- [135] Joshua Robinson, Ram Swaminathan, and Edward W. Knightly. Assessment of urban-scale wireless networks with a small number of measurements. *ACM MobiCom '08*.
- [136] James Roskind and Robert Tarjan. A note on finding minimum-cost edge-disjoint spanning trees. *Mathematics of Operations Research*, 10, 1985.
- [137] D. Krizanc S. Durocher, E. Kranakis and L. Narayanan. Balancing traffic load using one-turn rectilinear routing. In *TAMC*, April 2008.
- [138] P. Santi. The critical transmitting range for connectivity in mobile ad hoc networks. *Mobile Computing, IEEE Trans. on*, 4(3), 2005.
- [139] C. E. Shannon. A mathematical theory of communication. *Bell system technical journal*, 27, 1948.
- [140] Gaurav Sharma, Ravi R. Mazumdar, and Ness B. Shroff. On the complexity of scheduling in wireless networks. In *MobiCom '06*. ACM.
- [141] S. Sharma and D. Teneketzis. An externality-based decentralized optimal power allocation scheme for wireless mesh networks. *Sensor, Mesh and Ad Hoc Communications and*

- Networks, 2007. SECON '07. 4th Annual IEEE Communications Society Conference on*, pages 284–293, June 2007.
- [142] Scott Shenker, Sylvia Ratnasamy, Brad Karp, Ramesh Govindan, and Deborah Estrin. Data-centric storage in sensornets. *SIGCOMM Comput. Commun. Rev.*, 33:137–142, January 2003.
 - [143] A.P. Snow, U. Varshney, and A.D. Malloy. Reliability and survivability of wireless and mobile networks. *Computer*, 33(7):49–55, July 2000.
 - [144] Jungmin So and Nitin H. Vaidya. Routing and channel assignment in multi-channel multi-hop wireless networks with single network interface. In *The Second International Conference on Quality of Service in Heterogeneous Wired/Wireless Networks (QShine)*, 2005.
 - [145] Yang Su and Thomas Gross. Validation of a miniaturized wireless network testbed. In *WiNTECH '08: Proceedings of the third ACM international workshop on Wireless network testbeds, experimental evaluation and characterization*, pages 25–32, New York, NY, USA, 2008. ACM.
 - [146] A.P. Subramanian, H. Gupta, and S.R. Das. Minimum interference channel assignment in multi-radio wireless mesh networks. *Sensor, Mesh and Ad Hoc Communications and Networks, 2007. SECON '07. 4th Annual IEEE Communications Society Conference on*, pages 481–490, June 2007.
 - [147] Yusuke Takahashi, Yasunori Owada, Hiraku Okada, and Kenichi Mase. A wireless mesh network testbed in rural mountain areas. In *WinTECH '07: Proceedings of the the second ACM international workshop on Wireless network testbeds, experimental evaluation and characterization*, pages 91–92, New York, NY, USA, 2007. ACM.
 - [148] Diane Tang and Mary Baker. Analysis of a local-area wireless network. In *MobiCom '00: Proceedings of the 6th annual international conference on Mobile computing and networking*, pages 1–10, New York, NY, USA, 2000. ACM.
 - [149] L. Tassiulas and A. Ephremides. Stability properties of constrained queueing systems and scheduling policies for maximum throughput in multihop radio networks. pages 2130–2132 vol.4, dec 1990.
 - [150] Kevin Thompson, Gregory J. Miller, and Rick Wilder. Wide-area internet traffic patterns and characteristics. *IEEE Network*, 11:10–23, 1997.
 - [151] W. T. Tutte. On the problem of decomposing a graph into n connected factors. *Journal of the London Mathematical Society* 36, 1961.
 - [152] Guoqiang Wang and D.C. Marinescu. Cross-layer information sharing for wireless networks with asymmetric links. In *Wireless Pervasive Computing, 2008. ISWPC 2008. 3rd International Symposium on*, pages 475–479, may 2008.

- [153] Kuang-Ching Wang, Gayatri Venkatesh, Sajindra Pradhananga, Sandeep Lokala, Shari Carter, Jason Isenhower, and James Vaughn. Building wireless mesh networks in forests: antenna direction, transmit power, and vegetation effects on network performance. In *WiNTECH '08: Proceedings of the third ACM international workshop on Wireless network testbeds, experimental evaluation and characterization*, pages 97–98, New York, NY, USA, 2008. ACM.
- [154] Qin Wang, M. Hempstead, and W. Yang. A realistic power consumption model for wireless sensor network devices. In *Sensor and Ad Hoc Communications and Networks, 2006. SECON '06. 2006 3rd Annual IEEE Communications Society on*, volume 1, pages 286 –295, september 2006.
- [155] A. Warriier, S. Janakiraman, Sangtae Ha, and I. Rhee. Diffq: Practical differential backlog congestion control for wireless networks. pages 262 –270, april 2009.
- [156] Daniel Wu, Dhruv Gupta, Stephanie Liese, and Prasant Mohapatra. Qurinet: quail ridge natural reserve wireless mesh network. In *WiNTECH '06: Proceedings of the 1st international workshop on Wireless network testbeds, experimental evaluation & characterization*, pages 109–110, New York, NY, USA, 2006. ACM.
- [157] Fei Xing and Wenye Wang. On the critical phase transition time of wireless multi-hop networks with random failures. *ACM MobiCom '08*.
- [158] Yongqiang Xiong, Qian Zhang, Feng Wang, and Wenwu Zhu. Power assignment for throughput enhancement (pate): a distributed topology control algorithm to improve throughput in mobile ad-hoc networks. *Vehicular Technology Conference, 2003. VTC 2003-Fall. 2003 IEEE 58th*, 5:3015–3019 Vol.5, Oct. 2003.
- [159] Ning Xu. A survey of sensor network applications. *IEEE Communications Magazine*, 40, 2002.
- [160] Yong Yang, J.C. Hou, and Lu-Chuan Kung. Modeling the effect of transmit power and physical carrier sense in multi-hop wireless networks. *INFOCOM 2007. 26th IEEE International Conference on Computer Communications. IEEE*, pages 2331–2335, May 2007.
- [161] L. Ying, Shakkottai S., Reddy A., and S. Liu. On combining shortest-path and back-pressure routing over multihop wireless networks. *Networking, IEEE/ACM Transactions on*, PP(99):1, 2010.
- [162] Hongqiang Zhai and Yuguang Fang. A distributed packet concatenation scheme for sensor and ad hoc networks. pages 1443 –1449 Vol. 3, oct. 2005.
- [163] Alexander Zimmermann, Mesut Gunes, Martin Wenig, Ulrich Meis, and Jan Ritzerfeld. How to study wireless mesh networks: A hybrid testbed approach. In *AINA '07: Proceedings of the 21st International Conference on Advanced Networking and Applications*, pages 853–860, Washington, DC, USA, 2007. IEEE Computer Society.

- [164] Alexander Zimmermann, Mesut Günes, Martin Wenig, Jan Ritzerfeld, and Ulrich Meis. Architecture of the hybrid mcg-mesh testbed. In *WiNTECH '06: Proceedings of the 1st international workshop on Wireless network testbeds, experimental evaluation & characterization*, pages 88–89, New York, NY, USA, 2006. ACM.

APPENDIX

Appendix A

The maximum edge weight of any Euclidean minimum spanning tree of a set of nodes is the Compow weight of the set of nodes.

Proof: Let V be a set of nodes placed on a plane using an arbitrary distribution. Let $G_U = (V, E, r)$ denote a unit disk graph on V . There exists an edge from node u to node v if their Euclidean distance $d_{uv} \leq r$. The weight of an edge in E is the Euclidean distance between the endpoints of the edge. Now, let $G_c = (V, E, r_{min})$ denote the Compow graph of V where r_{min} is the minimum Euclidean distance such that G_c has only one connected component (all nodes in V are connected). We are interested in proving that r_{min} is the maximum edge weight of any Euclidean minimum spanning tree on V .

The proof proceeds in two steps. In the first step, it is shown there exists a minimum weight spanning tree in the Compow graph G_c which is also a minimum weight spanning tree on V . In the second step, it is shown that any minimum spanning tree on V also minimizes the maximum edge weight across all minimum spanning trees.

Part 1: By definition, G_c contains a minimal set of edges (E_c) such that weights of all edges are no more than minimum required to remain connected. This leads to two characteristics of G_c . First, all edges of maximum weight in G_c form a *disconnecting set* of edges whose removal will cause disconnection of G_c . Second, all minimum spanning trees in G_c have at least one of the maximum weight edges. We use these two properties to prove that there exists a minimum weight spanning tree in the Compow graph G_c which is also a minimum weight spanning tree on V .

Let T_c be a minimum weight spanning tree in G_c and T be a minimum weight spanning tree on V . We show first that there exist T and T_c such that maximum edge weight $\max(T) = \max(T_c)$. Then it is shown that T_c is also a minimum weight spanning tree on V . (Proof by contradiction) If $\max(T) > \max(T_c)$, there exists an edge $e_c \in G_c$ which can connect the end points of edge in T with weight $\max(T)$, yielding new minimum weight spanning tree (say T') on V . The overall weight of T' is lesser than T , which contradicts with the fact that T is a minimum weight spanning tree. So, $\max(T) \not> \max(T_c)$. Now, if $\max(T) < \max(T_c)$, there

exists a lower weight edge which can connect the endpoints of edge with weight $\max(T_c)$ in G_c . If so, T_c can not be minimum weight spanning tree in G_c and set of maximum weight edges also do not form a disconnecting set in G_c . Based on this contradiction, $\max(T) \not\leq \max(T_c)$. Hence, $\max(T) = \max(T_c)$. Since all edges in G_c are of lesser or equal weight than $\max(T_c)$, there exists a T on V such that $T = T_c$. This way, there exists a minimum weight spanning tree in the Compow graph G_c which is also a minimum weight spanning tree on V .

Part 2: Any minimum spanning tree on V also minimizes the maximum edge weight across all minimum spanning trees.

Proof (by contradiction) - Suppose T_1 is a minimum spanning tree on V . Also suppose that there exist another minimum spanning tree T_2 which minimizes maximum edge weight. Since T_1 does not minimize the maximum edge weight, there must be an edge (say e_1) in T_1 which is of higher weight than all edges in T_2 . Removing e_1 from T_1 will create a forest with exactly 2 trees. Now we must find an edge (say e_2) in T_2 which can connect two trees of T_1 forest. Since e_1 was of higher weight than all edges of T_2 , new connected tree T_1 which contains e_2 has total lower overall weight. This contradicts with the fact that T_1 was a minimum spanning tree. Hence, proved that T_1 also minimizes maximum edge weight in all minimum spanning tree. (or put another way, maximum weight edge in any minimum spanning tree is also maximum across all minimum spanning trees). This can also be stated as, let $\max(MST)$ denote the maximum edge weight in a minimum spanning tree, there will be at least one edge in all minimum spanning trees which has weight $\max(MST)$.

Since every minimum spanning tree on V has an edge with weight $\max(MST)$, and G_c contains a minimum spanning tree of V , it is proven that the maximum edge weight of any minimum spanning tree of a set of nodes is the Compow weight of the set of nodes.