Cognitive Routing for Wireless Ad Hoc Networks

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PhD Thesis

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August 2011

Abstract

This thesis examines the design of cognitive routing to improve wireless ad hoc network performance in terms of throughput and delay, as well as reducing the impact of relaying on the network, without deteriorating end-to-end capacity. Routing metrics are designed to replace the conventional shortest path routing metric (hop count) used in many existing routing protocols (e.g. AODV, DSR and DSDV). The routing metrics take into account a node/link's surrounding environment conditions (such as disturbed node number, bottleneck capacity, and channel utilization).

A new family of Disturbance/Inconvenience based Routing (DIR) metrics are proposed initially, which takes both inward and outward interference into account in their weight metric designs, in order to reduce the impact of interference in the crowded areas. Then, a Bottleneck-Aware Routing (BAR) metric is developed to reduce bottleneck node problems for wireless ad hoc networks. BAR not only takes an individual node's interference and capacity into account but is also aware of the location of bottleneck nodes such that routes can be intelligently established to avoid congested areas, and especially avoid bottlenecks. Under low traffic load conditions, both metrics show a significant reduction in the congestion levels compared with the shortest path routing metric despite increasing the relaying burden on nodes in the network.

Taking these findings into account, a cross-layer design is developed, where a Cognitive Greedy-Backhaul (CGB) routing metric is combined with a Reinforcement Learning based Channel Assignment Scheme (RLCAS). By applying a reinforcement learning algorithm to the channel assignment scheme, channels can be assigned through a more distributed and efficient approach. Moreover, the hidden node problem is mitigated and better channel spatial reuse is achieved due to the learning within the channel assignment scheme. By obtaining cross-layer information from the channel assignment scheme, CGB incorporates channel utilization into its metric in order to build backhaul links, while still utilising relatively short paths to help reduce the relaying burden. Thus, two significant advantages can be achieved using this cross-layer design: limiting the relaying impact and maintaining network capacity for wireless ad hoc networks. Results

show that this cross-layer design outperforms the other schemes in terms of energy consumption, throughput and delay under varying traffic loads. Furthermore, the learning progress of RLCAS is studied in a multi-hop scenario and the reason why the learning engine of RLCAS performs well when it is associated with the CGB routing metric is also provided.

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Acknowledgements

I would like to dedicate this thesis to my parents, as it is their continued endless love and encouragement that has enabled me to progress my study in UK up to 9 years until the completion of this PhD thesis.

I would especially like to thank my first supervisor, Dr. David Grace for his invaluable advices, constant technical support and insight throughout my PhD research.

I am also grateful to my second supervisor Dr. Paul Mitchell who offered me very useful comments and suggestions on this research work.

Further thanks go to my colleagues in the Communication Research Group for providing a pleasant environment to work and useful discussions. In addition, my life in the University of York could not be this fantastic and cheerful without the CSSA (Chinese Student Society Association) and Wentworth College football team.

Finally, I would like to express my deepest thankfulness to my wife Haiqi Li, who has been sharing happiness and facing difficulties with me.

Declaration

Some of the research in this thesis has been published in or submitted to conference proceedings and journals. These papers are shown below.

- Bo Han, David Grace, Paul Mitchell, ***A Cognitive Cross-layer Design for Wireless Ad Hoc Networks***, Submitted to Ad Hoc Networks Journal, 2011.

- Bo Han, David Grace, Paul Mitchell, ***Exploring Reinforcement Learning Channel Assignment with Cognitive Routing for Wireless Ad Hoc Networks***, in preparation for IET Communications, 2012.

- Bo Han, David Grace, and Paul Mitchell, ***Cognitive Greedy-Backhaul Routing Metric Exploiting Cross-layer Design for Wireless Ad Hoc and Mesh Networks***, presented at Cognitive Radio Oriented Wireless Networks & Communications (CROWNCOM), 2010.

- Bo Han and David Grace, ***Using Cognitive Interference Routing to Avoid Congested Areas in Wireless Ad Hoc Networks***, presented at Proceedings of 18th International Conference on ICCCN 2009.

- Bo Han, David Grace, and Paul Mitchell, ***Using Bottleneck Aware Routing to Improve End-to-End Bottleneck Capacity for Wireless Ad Hoc Networks***, presented at Karlsruhe Workshop on Software Radios (WSR), Karlsruhe, Germany, March, 2010.

All contributions presented in this thesis as original are, to the best knowledge of the author. Acknowledgements and references to other researchers have been given as appropriate.

Chapter 1

1 Introduction

Contents

1.1 Background of Wireless Ad Hoc Networks

A rapid, self-configurable and decentralized wireless system is required for communication service in rescue/emergency operations, military conflicts, environment monitoring and natural disasters. Such network scenarios cannot depend on a centralized network with organized connectivity, but they can be achieved by the creation of wireless ad hoc networks, which are a decentralized type of wireless network which can be created without any established infrastructure or centralized administration. In wireless ad hoc networks, nodes are capable of functioning as routers that are not only able to receive, but can also transmit and forward packets [1].

There are different types of wireless ad hoc networks that are classified according to their applications. For instance, a mobile ad hoc network (MANET) is a self-configuring network of mobile devices that is created via wireless links without using centralized administration or existing network infrastructure. The network topology changes unpredictably since the mobile nodes may move randomly in a MANET. One typical example of applying MANETs is for communication amongst vehicles and between vehicles and roadside units which aims to reduce car accidents via inter-vehicle communications [2]. Another type of wireless ad hoc network is a wireless sensor network (WSN) which in devices are sensor nodes that have less mobility compared with MANETs and they are normally deployed in distributed locations for monitoring environment conditions by conveying information on a hop-by-hop basis. For example, sensor nodes can be placed in a forest to detect fires, and they can also be used to reduce electricity/energy cost in a smart building as sensors can make the utilities more efficient by monitoring the surroundings [3]. In addition, a wireless mesh network (WMN) is another type of wireless ad hoc network where a hierarchical architecture is required as mesh clients need to forward traffic to and from the gateways via access points (mesh routers) in order to connect to the Internet. Unlike a MANET, where end hosts and routing nodes are quite distinct and dynamic, mesh routers are usually stationary. Therefore, due to the hierarchical architecture and stable topology, a WMN can provide higher bandwidth and reliability than MANETs and WSNs [4]. These different types of networks have some similarities: they are all distributed wireless networks which use an ad hoc method as nodes are used to forward data for other nodes. Due to the multi-hop feature of these networks, the purpose of this thesis is to investigate how the impact of relaying can be reduced in wireless ad hoc networks by examining routing metrics and network design while still maintaining network performance such as capacity, throughput and delay.

1.2 Advantages and Limitations of Wireless Ad Hoc Networks

Compared with cellular networks, wireless ad hoc networks are an autonomous collection of mobile nodes which are deployed in a distributed method since there is no need to build centralized infrastructures. Therefore, a wireless ad hoc network is a self-configuring/healing network that can be deployed rapidly as mobile devices can join or leave the network without jeopardizing the connectivity of the overall system. The network size and communication services can be extended simply by deploying more ad hoc nodes due to their multi-hop feature. Moreover, this type of network is more reliable and resilient as each node connects to several other nodes; thus, the overall communication system is not affected by a single node's failure since its neighbours are able to find an alternative route using a reliable routing protocol [3, 5, 6].

Along with these great advantages, wireless ad hoc networks also suffer some limitations [7-11]. For instance, the network lifetime is a problem for battery-limited portable devices, especially WSNs, as sensors are normally placed in extreme environments such as volcanoes, oceans and forests where battery recharge or replacement is not easy to perform. In addition, the frequent and unpredictable movement of mobile users may result in a lack of topology information; consequently, this can result in route oscillation and packet loss problems. The lack of centralized monitoring also means that it may be difficult to identify incorrect operations, e.g. broken links and selfish behaviour. Wireless ad hoc networks are more complex due to the heterogeneous node types as each node may be equipped with different numbers or types of radio interface that have varying transmission range or capacities. Moreover, complex network protocols and algorithms are required for this kind of heterogeneity. In [12], Gupta and Kumar also found that wireless ad hoc networks are considered to be not scalable as efficiency falls rapidly with the increasing size of the network due to the requirement of extra relaying for maintaining communication services that are far away. This is because the limited resources are shared not only with originating traffic but also with the relaying traffic that is required to forward the traffic on the behalf of other nodes.

1.3 Overview of Wireless Ad Hoc Routing

Routing is a key feature of packet-switched networks (such as in the internet) as it enables messages (packets) to be passed though the network from one point to another and eventually to reach the destination [13]. The process of selecting paths to send the traffic through the network is not only important to wired networks but also it is a core problem in wireless networks. For wireless ad hoc networks, routing is much more complex than in traditional wireless systems, due to the lack of centralized control and knowledge of a predetermined topology. In order to convey messages from source node to destination node, two choices have to be made: the routing protocol and routing metric. The routing metric is used to select a path according to a specific design constraint out of all available choices. The routing protocol specifies how nodes disseminate information so that network topology can be discovered and maintained to select routes between two nodes [14]. In other words, the routing metric is used to calculate which route is the best to take among those available route opportunities that are discovered by the routing protocol depending on its metric. An example of a metric is the weight value which is learned and assigned by the routing protocol to links/nodes. A higher weight value of a link indicates higher cost of using the link.

In wireless ad hoc networks, initially nodes are not familiar with the topology of their networks and have to discover the topology. Ad hoc networking protocols are mainly divided into three classes: proactive (table-driven), reactive (on-demand) and hybrid (both proactive and reactive) protocols. In a proactive protocol, each node has an advanced knowledge of available routing information from other nodes as routing table updates are periodically transmitted throughout the network [15, 16]. Therefore, a proactive protocol is more effective on route establishment as routing information is available at each source node. Examples of proactive protocols are DSDV [17], WRP [18], FSR [19], OLSR [20] etc. In contrast, as in the name of protocol (on-demand), the route discovery process only takes place whenever a node has a data packet to send such as AODV [21], DSR [22], TORA [23], ABR [24], ARA [25]. In general, proactive protocols update route information independently of the network traffic whereas the route discovery process of a reactive protocol is triggered depending on network traffic. The hybrid protocol combines both proactive and reactive protocols, for example: ZRP [26]. Initially, ZRP functions as a proactive protocol to find routes based on periodic updates, and then it floods the requests of route finding on the demand of activating nodes as a reactive protocol.

Both proactive and reactive protocols have their advantages as well as disadvantages. Proactive protocols have better knowledge of routing information to all destinations, therefore result in a rapid process of route establishment. Moreover, they react faster to topology changes due to their consistent up-to-date route discovery process. Nonetheless, they consume network capacities for nodes that are not in use and have a significant control overhead in generating routing information for maintaining the network topology. On the other hand, reactive protocols save bandwidth and energy due to the comparatively fewer activities in the route discovery process although they create a longer delay when discovering routes. Under a high traffic load, networks can be congested by the flooding of route request packets due to the high demands of route finding. For a hybrid protocol, although it could have both the advantages of proactive and reactive protocols, performance is mainly limited by the number of active nodes and it generates more complexity for the route discovery process since it is using both proactive and reactive techniques.

Since the routing protocols can discover the network topology and available relaying choices, another challenge of routing is to determine which paths are suitable to select among all the options. There are many different routing metrics available in wireless ad hoc networks, such as number of hops, link utilization, latency, packet loss, energy, throughput, interference, load-balancing and so on. By manipulating link cost/weight, routes can be selected differently with varying routing metrics to achieve different goals. Lots of routing metrics have been proposed for wireless ad hoc networks, such as *hop count* [21, 22], *ETX* [27], *ETT* [28], *WCETT* [28], *ENT* [29] etc. More details of these listed metrics will be reviewed in the next chapter.

1.4 Purpose of the Thesis

As aforementioned, wireless ad hoc networks have been suggested as a method of peer-to-peer communications, removing the need for fixed infrastructures. Such methods work well when the number of relay hops is small, but their efficiency falls rapidly in homogeneous ad hoc networks when the number of relay hops increases, due to the fact that additional capacities are required to carry information on a hop-by-hop basis. The capacity is considered to be surprisingly low in wireless ad hoc networks [30].

Many works focused on the design of efficient routing protocols to deal with moving nodes and topology maintenance due to the dynamic features of wireless ad hoc networks. Less attention has been paid on the choice of routes in wireless ad hoc networks. Therefore, this thesis is to investigate how the impact of relaying can be reduced in wireless ad hoc networks by examining routing metrics and channel assignment schemes while still maintaining network capacity with increasing traffic loads.

1.5 Cognition Concept

To understand the term ‘cognitive routing’, which is one of the main aspects of this thesis, it is necessary to introduce two related subjects – cognitive radio and cognitive networks.

1.5.1 Cognitive Radio

Cognitive radio has been proposed as a paradigm for wireless communications that can utilize the radio frequency spectrum in a more efficient way as it has the ability to change its transmitter parameters (operating spectrum, modulation, transmit power) based on interactions with the surrounding spectral environment [31]. Based on the cognitive concept, the cognitive radio technique provides the opportunity for unlicensed users to share the radio spectrum with licensed users without degrading their services [32].

The fundamental objective of cognitive radio is to identify sub-bands of the radio spectrum that are currently unemployed and assign them to unlicensed secondary users [33]. In order to extend this concept to include interaction with the environment, a cognition cycle is introduced. Figure 1-1 shows the cognition cycle. By the process of observing the environment, orienting itself, creating plans, then deciding and acting, the cognitive radio can finally achieve its goals [31, 34].

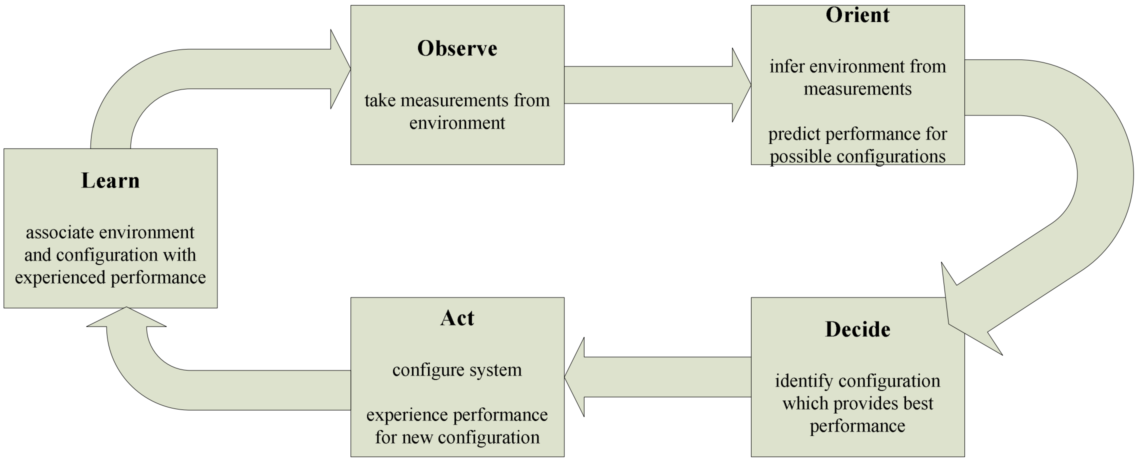


Figure 1-1 Cognition cycle of cognitive radio

1.5.2 Cognitive Network

Modern communication networks face challenges on the efficient management of increasing complexity as networks are composed of many heterogeneous nodes, links and users. In addition, those networks are often operating under dynamic environments where network resources (e.g. node energy and channel assignment), application data (e.g. the location of data) and user behaviours (e.g. user mobility) change over time [35]. All those factors can degrade network performance and they are beyond the limit of manual administration. In order to maintain a good quality service based on as little human intervention as possible, a cognitive network paradigm is proposed [36, 37]. A cognitive network is a network with a cognitive process that can perceive current network conditions, and then plan, decide and act on those conditions. The network can learn from these adaptations and use them to make future decisions, all the while taking into account the end-to-end goals [38].

Cognitive networks should be self-aware and have a self-managing ability that means they should have knowledge about themselves as well as their own environment, and can plan and execute appropriate actions in a decentralized way. The self-aware feature of a radio is claimed to be 'cognitive' in [31]. Extending this cognition concept beyond the radio domain (layer *1* and layer *2*) to cover all the layers of the OSI model is the difference between cognitive radio and cognitive networks.

The definition is similar to the definition of cognitive radio as both of them need to learn, adapt and react to their environment to achieve a certain goal, but the performance of the cognitive network is measured by end-to-end rather than point-to-point.

1.5.3 Cognitive Routing

Before introducing the term "cognitive routing", some general concepts about routing are presented to help the reader to understand the ideas. Routing is a process of selecting paths. In order to serve goal of the network level (e.g. finding the shortest path), there must be a certain mechanism to comprehensively link the nodes in the network and allow them to establish routes in a collective way.

Conventional routing algorithms normally find the route with the shortest path to improve efficiency [28]. However, in a wireless ad hoc network, shortest path routing is not necessarily the best solution. First of all, more efficient routing metrics can be achieved by taking other factors into account, such as capacity, delay, link length, spectrum availability, power throughput and/or interference rather than just considering hop number. Figure 1-2 demonstrates a case where the longer route in terms of hop number (dashed path) is preferred due to its higher link capacity than the short route (solid path) as the thick dotted lines indicate higher capacity due to a high level of interference caused at node C in this graph. The longer link is better as the links with higher capacity can carry more relaying traffic and can reduce the burden of bottleneck(s) in the network. Also, regarding the complicated radio environment due to interference, a longer route could be a better choice than a short route, if the node on the shorter route suffers/causes more severe interference from/to other node(s) (see Figure 1-3). If a node suffers from serious interference, it could significantly decrease the effective capacity for the routing traffic request; if it causes too much interference to neighbouring nodes, others may suffer a great deal in terms of effective capacity [39].

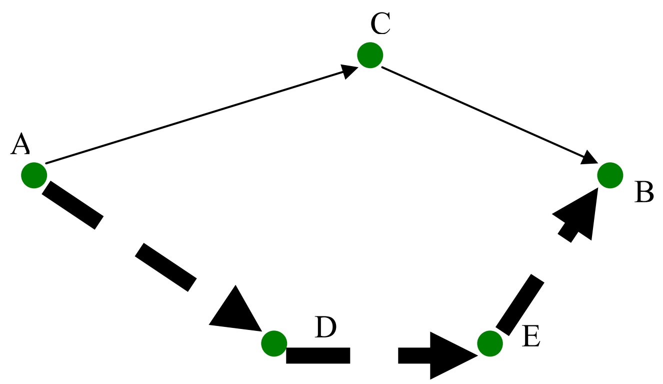


Figure 1-2 Capacity routing: dotted route shows better result in terms of capacity

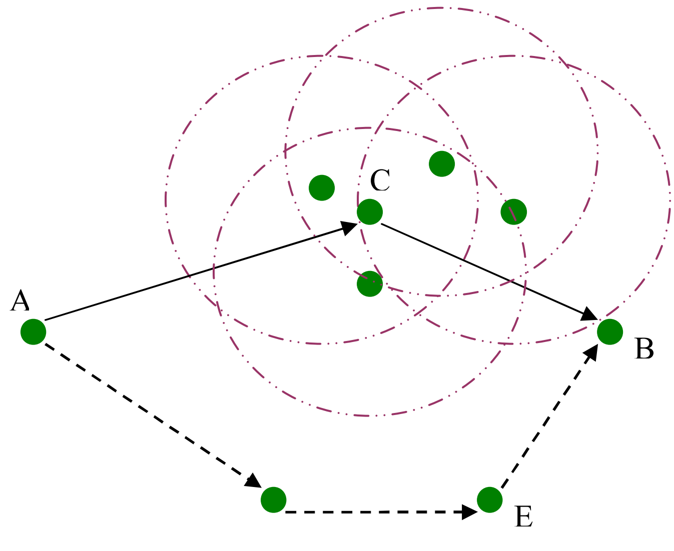


Figure 1-3 Interference routing

As aforementioned, a cognitive radio 'is a radio that can change its transmitter parameters based on interaction with the environment where it operates' [11], and additionally relevant here is the radio's ability to look for, and intelligently assign, spectrum 'holes' on a dynamic basis from within primarily assigned spectral allocations. A cognitive network 'is a network with a cognitive process that can perceive current network conditions, and then plan, decide, and act on those conditions' [10]. Given the combination of cognitive radio and cognitive networking aspects in this thesis, we refer to this collective process as cognitive routing. For the routing mechanism to be 'cognitive', it must have three types of process: observing, reasoning (calculating) and acting (adapting) [14, 15]. In this thesis, we focus on the calculating process mainly, assuming the necessary information for each node is available through observing and different adjustments can be carried out in terms of acting.

Due to the aforementioned cognitive concept, here we define cognitive routing as a routing selection process that not only can perceive and utilize varying link conditions based on its metric design (e.g. link distance between the transmitter and the receiver, interference, energy cost, channel capacity and loss rate), but also can improve network performance in the future by the decision of current route selection. As aforementioned, the purpose of this thesis is to design a routing metric that can reduce relay hops while still maintain network capacity by associating cognitive radio techniques. A reinforcement learning based channel assignment scheme is applied to assign channels in a decentralized manner. Therefore, in this thesis, the cognitive routing metric is specified to be able to perceive channel assignment or interference information, utilize it and improve the future learning efficiency of the channel assignment scheme by the current routing selection process. Cognitive greedy-backhaul (CGB) routing metric is an example of cognitive routing in Chapter 7 as it is not only aware of the channel assignment situation in the network, but more importantly it makes the reinforcement learning based channel assignment in a more efficient and faster way (results will be shown in Chapter 7).

1.6 Thesis Structure

The thesis is divided into 8 further chapters and the structure is outlined as follows.

Chapter 2 introduces the background information of this thesis which is a literature review on wireless ad hoc routing metric design. The review investigates, summarises and comments on those wireless ad hoc routing metric designs. In addition, routing protocols include DSDV (a proactive routing protocol), DSR and AODV (reactive routing protocols) are also described to help the reader to understand the routing process as a whole. Dijkstra's Algorithm is also presented as a technique to find the lowest cost path for all routing metric designs in this thesis.

Chapter 3 presents the simulation techniques and software tools that are used to conduct the research work. In addition, the verification methodology is provided along with the main parameters to evaluate the performance of the proposed routing metrics.

Chapter 4 reviews a routing metric design known as minimum impact routing (MIR) which aims to reduce the interference when selecting routes. It is then followed by a proposed family of interference based routing metric designs inspired by MIR, known as disturbance/inconvenience based routing (DIR) which can take both 'inward' and 'outward' interference into account. By manipulating a priority factor, routes can be selected in a more altruistic (outward) or selfish (inward) manner. Two classes of DIR have been given to study the interference on wireless ad hoc networks, DIR^k and $DIR_{threshold}$. A discussion of the interference of the two classes of DIR on network performance is also provided.

Chapter 5 illustrates the capacity model used in this thesis. It also presents a bottleneck node problem and its impact on wireless ad hoc networks. Then two routing metrics, capacity based routing (CBR) and bottleneck-aware routing (BAR) are studied to investigate how the bottleneck problem can be mitigated. Performance and conclusions are also given.

Chapter 6 proposes a cross-layer design by combining the routing metric with the channel assignment scheme to reduce the relaying burden while still maintaining bottleneck capacity. The cross-layer design starts with two simple channel assignment schemes. Simulation and results are also given to illustrate the importance of the channel assignment scheme for this cross-layer design.

In chapter 7, a practical network model is developed by including a more realistic network environment, including more sophisticated propagation, interference, traffic and energy models. A sensing based channel assignment scheme and a reinforcement learning based channel assignment scheme are also introduced to perform the cross-layer design with varying routing metrics. In addition, time sharing and MAC schemes are also embedded in to the network. Network performance is tested when applying the reinforcement learning based channel assignment scheme with varying routing metric designs. One of the routing metric designs, CGB, is analysed to illustrate the reason why it can perform an efficient learning process on channel selections with a reinforcement learning based channel assignment scheme.

Rather than analyse the network performance by examining reinforcement leaning based channel assignment schemes with different routing metric designs as in Chapter 7, chapter 8 looks at a different perspective by using varying channel assignment schemes with the same routing metric design. A pure sensing based channel assignment scheme, pure reinforcement learning based channel assignment scheme (without the assistance of any sensing technique) and a reinforcement learning based channel assignment scheme plus sensing are all associated with the CGB routing metric. Network performance is tested for the schemes in terms of throughput and delay.

Chapter 9 describes modifications, improvements and potential work that may further improve the capacity of wireless ad hoc networks. This is followed by the overall summary and conclusions in chapter 10.

Chapter 2

2 Wireless Ad Hoc Routing Metrics – A Literature Review

Contents

2.1 Introduction

This chapter provides the relevant background information to the research work. Initially we categorize wireless ad hoc routing metric designs into two types: non-link quality based routing and link quality based routing. The literature review of each type of routing metric is shown. Then several well-known wireless ad hoc routing protocols are discussed to aid understanding of the routing process. A discussion of which type of routing protocol is more applicable to associate with our proposed routing metrics is also presented.

2.2 Link Quality Based Routing Metrics

ETX is designed to make the routing metric aware of link quality rather than just the simple hop count in order to improve network performance. The awareness of link quality is considered to be favourable for routing metric design in multi-hop wireless networks especially for ad hoc and mesh networks. Consequently, a large number of routing metrics are modified or extended based on ETX to improve routing metric design by considering other factors (interference, channel diversity, load balancing etc.). Here, we will give a literature review on the most significant link quality routing metrics such as ETX, ETT, WCETT, MIC, iAWARE etc.

2.2.1 ETX

Expected Transmission Count (ETX) [27] was the first mesh metric design to take link quality into account in multi-hop wireless networks. The ETX of a link is defined as the expected number of data transmissions that are needed for successfully delivering a packet over that link. It is proposed to find high-throughput paths by taking link delivery ratios of both forward (d_f) and reverse (d_r) direction into account. The metric is defined as below.

$$ETX = \frac{1}{d_f \cdot d_r} \tag{2.1}$$

The path is selected based on the minimum sum of ETX along the route to the destination. Since each node periodically broadcasts probe packets to its neighbours, the delivery ratio (d_f and d_r) can be measured by the number of received probes (at the receiver or transmitter respectively) at the last T time interval in a sliding window fashion.

ETX is also an isotonic routing metric. It takes into account delivery ratios which directly affects throughput as well as loss ratio asymmetry in both directions of each link since loss ratio equals one minus the delivery ratio. In addition, the metric reflects the effect of both loss ratio and path length. However, ETX does not cope well with a network which has a high transmission data rate and larger packet size due to the fact that broadcasts are normally performed at the network basic rate and probe packets are relatively small, so that the metric cannot reflect the loss rate of actual traffic. In addition, the metric does not consider load-balancing and does not take any channel conditions into account [14, 40-43].

2.2.2 ETT

Expected Transmission Time (ETT) is proposed as a “bandwidth-adjusted ETX” by Draves et al. [28]. The metric is a function of the loss rate and the bandwidth of a link and it improves the ETX metric by further considering the differences in link transmission rates. The function of ETT is defined below.

$$ETT = ETX \cdot \frac{S}{B} \tag{2.2}$$

Where S indicates the size of a probing packet and B is the bandwidth of the link. The ETT metric modifies the ETX metric by multiplying by the time spent in transmitting the packet.

Therefore, ETT has the advantages of ETX as well as the improvement of taking link capacities into consideration to increase the throughput on the path. Nonetheless, the disadvantages of ETT remain, in that the metric does not take account link load, path length and channel diversity.

2.2.3 mETX and ENT

Koksal and Balakrishnan [44] proposed another two link quality-aware routing metrics mETX and ENT which are modified versions of ETX. The ETX routing metric is considered to work well in relatively static wireless channel conditions as it uses the mean loss ratios in making route decisions and packet loss probability shows a significant long-term dependence [40]. However it has a shortcoming to cope with short term channel or fast link-quality variations, e.g., it cannot adapt well to burst loss conditions even with a low average packet loss ratio of the channel due to its high variability.

mETX is defined as follows:

$$mETX = \exp\left(\mu_{\Sigma} + \frac{1}{2}\sigma_{\Sigma}^{2}\right) \tag{2.3}$$

where μ_{Σ} indicates the estimated average packet loss ratio of a link; σ^{2}_{Σ} is the variance of this value. These two parameters of a channel are estimated by considering the locations of errored bits in each probe packet. A loss rate sample is calculated for every ten probe packets that are sent out by each node like ETX [27].

Unlike ETX and mETX, ENT also considers the number of retransmissions into the routing metric design which limits route computation to links that show an acceptable number of retransmissions according to upper-layer requirements. The ENT routing metric is defined as follows:

$$ENT = \exp\left(\mu_{\Sigma} + 2\delta\sigma_{\Sigma}^{2}\right) \tag{2.4}$$

where δ indicates the certain threshold number of retransmissions which will determine the link layer protocol's decision to give up a sending attempt.

The time-varying characteristics of a wireless channel are captured by both of the mETX and the ENT and they could be directly translated into network and application layer quality constraints [44].

2.2.4 WCETT

Draves et al. also proposed a Weighted Cumulative ETT (WCETT) [28] which is an extended version of ETT considering end-to-end delay and channel diversity. Therefore, the metric is composed of two parts as shown below.

$$WCETT = (1-\beta)\sum_{i=1}^{n} ETT_i + \beta \max_{1\le j\le k} X_j \tag{2.5}$$

Where n is the number of hops along the path; k is the total number of channels available in the system; X_j is the sum of transmission times of hops on channel j; finally, β is a tuneable parameter which is between *0* and *1* .This separates the priority impact of different parts of the weight function. The first part of the function $\sum_{i=1}^{n} ETT_i$ enables WCETT to account for the estimated end-to-end delay experienced by a packet travelling along the path over n hops. Since neither ETX nor ETT is designed for multiple-channel networks, simply adding up the ETT of each individual link cannot reflect an optimum path in a multi-channel network due to the intra-flow interference which can reduce the overall performance of the entire path. Therefore, in order to account for the channel diversity in multi-channel networks, the second part of the function $\max_{1\le j\le k} X_j$ is included to reflect the sum of transmission times on the bottleneck channel due to its heavy usage. Consequently, it shows the feature that a path with more channels assigned on their links is preferable due to the lower weights.

Although WCETT takes intra-flow interference into its metric design, the metric does not explicitly consider inter-flow interference. Hence, it may lead activated traffic flows to congested areas. Moreover, the metric is not isotonic which may not guarantee a shortest path. An example topology is shown in Figure 2-1 which illustrates that Dijkstra's algorithm cannot find the shortest path based on the isotonic routing metric of WCETT. Considering the path from S→A→B, the estimated end-to-end delay is *0.4* as ETT from S→A is *0.2* and ETT from A→B is *0.2*, and $\beta \max_{1\le j\le k} X_j$ is *0.2* as both channel *2* and channel *3* has same delay of *0.2*. Therefore, the WCETT of path S→A→B is *0.3* when β is *0.5*. Considering the path from S→B directly, the WCETT is *0.45*. Therefore, Dijkstra's algorithm will go through the path S→A→B rather than S→B directly due to the smaller WCETT value. However, considering a path is required from S to D and the link from B to D also uses channel 3, then $\max_{1\le j\le k} X_j$ (the sum of transmission times on the bottleneck channel) is changed significantly from *0.2* to *0.7*. Therefore, the correct shortest path should be from S→B→D due to the smallest WCETT value as shown in Table 2-1. However, WCETT incorrectly selects the other one (S→A→B→D) as Dijkstra's algorithm has determined the shortest path from S to B is through S→A→B.

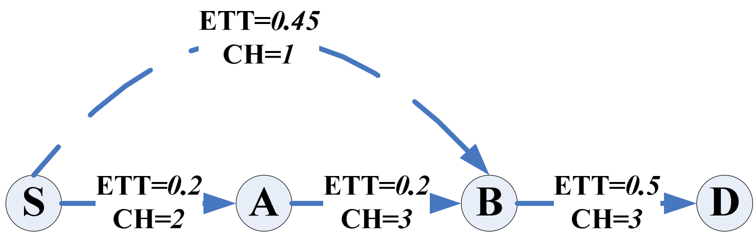


Figure 2-1 Example topology where Dijkstra's algorithm cannot find a optimum shortest path based on the isotonic routing metric WCETT

Path	$\sum_{i=1}^{n} ETT_i$	$\max_{1\le j\le k} X_j$	WCETT ($\beta = 0.5$)
S→B→D	*0.95*	*0.5*	*0.725*
S→A→B→D	*0.9*	*0.7*	*0.8*

Table 2-1 Shows the path WCETT value

Therefore, WCETT cannot be applied to all routing protocols as it is unable to find a shortest path and solve looping problem.

2.2.5 MIC

Yang et al. [45] proposed a metric of interference and channel-switching (MIC) in order to solve the issues of WCETT, which are non-isotonic routing and non-awareness of inter-flow interference. The weight path function of MIC is defined as:

$$MIC(p) = \alpha \sum_{link\ l \in p} IRU_l + \sum_{node\ i \in p} CSC_i \qquad \textbf{(2.6)}$$

where p stands for a path in the network, IRU and CSC stand for interference-aware resource usage and channel switching cost respectively, which are defined later. α is a trade-off value to make sure that the IRU is around the same value range as the value of CSC, and is defined as follows:

$$\alpha = \frac{1}{N \cdot \min(ETT)} \qquad \textbf{(2.7)}$$

where N indicates the number of nodes in the network and min(ETT) is the smallest ETT in the network, which can be estimated based on the lowest transmission rate of the wireless cards.

IRU (Interference-aware Resource Usage) captures the differences in the transmission rates, loss ratios of wireless links as well as the inter-flow interference, and CSC (Channel Switching Cost) captures the intra-flow interference. They are defined as follows:

$$IRU_l = ETT_l \cdot N_l \qquad \textbf{(2.8)}$$

$$CSC_i = \begin{cases} w_1 \; if \quad CH(prev(i)) \neq CH(i) \\ w_2 \; if \quad CH(prev(i)) = CH(i) \end{cases}, \quad 0 \leq w_1 < w_2 \qquad \textbf{(2.9)}$$

where N_l is the set of neighbour nodes that the transmission on link interferes with, *CH(i)* indicates the channel assigned for node *i*'s transmission and *prev*(*i*) presents the previous hop of node *i* along the path. The relationship of $w_2>w_1$ captures the fact that a higher cost is imposed if node *i* and *prev(i)* use same channel due to the intra-flow interference. In [45], w_1 is set to *0* and the value of w_2 is from *0.3* to *5*. Therefore, due to the component of *IRU*, MIC favours a path that consumes less channel times at its neighbouring nodes. The CSC part of MIC represents the metric's ability to deal with the intra-flow interference as it provides a higher weight value for the consecutive links if they use the same channel. Therefore, the path with more diversified channel assignments is preferred by the MIC.

It is worth mentioning that MIC is not isotonic if it is applied directly to real networks. Therefore, the authors [45] introduced virtual nodes which are images of real nodes into the network and thereafter guarantee the shortest loop-free path by decomposing MIC into isotonic link weight assignments on virtual links between these virtual nodes.

Although the MIC routing metric aims to account for inter-flow interference by scaling up the ETT of a link by the number of neighbours interfering with the transmission of that link, the interference level caused by each interferer node is not the same in practice as it depends on the SINR value at the receiver of the link (which includes the interferer's signal strength, locations with respect to the object link's receiver and path loss characteristics etc.). Moreover, the CSC part of MIC only considers the intra-flow interference when the links are consecutive. This is imprecise as interference can be 3-hops away along a same path due to the fact that interference range is always much larger than transmission range in real life [46].

2.2.6 iAWARE

The interference aware routing metric (iAWARE) [47], is proposed to capture the effect of variations of link loss ratio, differences in transmission rate as well as intra-flow and inter-flow interference. Unlike the MIC, the iAWARE metric captures the intra-flow and inter-flow interference using a physical interference model by calculating the signal to noise ratio (SNR) and signal to interference and noise ratio (SINR).

The link metric, iAWARE of a link i is defined as:

$$iAWARE_i = \frac{ETT_i}{IR_i} \tag{2.10}$$

where $IR_i(u)$ refers to an interference ratio of a node u in a link $i = (u,v)$ which is bigger than 0 and smaller or equal to 1 as defined:

$$IR_i(u) = \frac{SINR_i(u)}{SNR_i(u)} \tag{2.11}$$

Thus, considering a bidirectional communication link $i = (u,v)$ for a DATA/ACK-like communication, the interference ratio of a link i (IR_i) is defined as:

$$IR_i = \min(IR_i(u), IR_i(v)) \tag{2.12}$$

The weighted cumulative path metric $iAWARE(p)$ of a path p is defined as follows.

$$iAWARE(p) = (1-\alpha)\sum_{i=1}^{n} iAWARE_i + \alpha \max_{1 \le j \le k} X_j \tag{2.13}$$

where α is a tunable parameter set between 0 and 1; k is the number of orthogonal channels available; n is the number of hops along the path p; the part of X_j indicates that the iAWARE is aware of the channel diversity and the intra-flow interference as it is defined as:

$$X_j = \sum_{\text{Conflicting links } i \text{ on channel } j} iAWARE_i, \quad 1 \le j \le k \tag{2.14}$$

Although the iAWARE uses a practical interference model to continuously reproduce the neighbouring interference variations onto routing metrics, the routing metric is not isotonic due to the second component like WCETT.

2.2.7 Other Link Quality Based Routing

There are other link quality based routing metrics and although they are not as popular as the aforementioned link quality based routing metrics, they are introduced here to provide a broad background information of wireless ad hoc routing metrics.

In [48], Zhai et al. proposes a routing metric known as interference clique transmission time (CTT) to take account of the multi-rate capability (the capability of supporting multiple channel rates) with the packet loss ratio (ETX) in order to maximize the end-to-end throughput. Although this metric selects the path which has the maximum end-to-end bottleneck capacity, it produces an excessive relaying burden and it is not isotonic [49].

Genetzakis, et al. [49] proposes a contention-aware transmission time (CATT) metric which takes both contentions of the shared wireless channel and rate diversity in multi-radio multi-channels into account. The performance of using CATT is improved by using ETX and ETT as it captures both the number of interfering links and the level of their interference. In addition, it is an isotonic routing metric. However, the scalability of using CATT is not examined due to the limited number of test nodes and again it fails to take path distance into account.

The multi-channel routing (MCR) metric is proposed by Kyasanur et al. [50] to deal with multiple channel, multi-interface networks. The metric does not only select channel diverse paths like WCETT, but also modifies WCETT to incorporate switching cost, so that it prevents selecting paths that require frequent channel switching. The major limitation of this metric is that it does not completely account for inter-flow interference as all channels are considered as orthogonal [43].

Tsai et al. proposed a weighted interference multipath [51] metric which aims to achieve better reliability and low delay by taking the path interference (which reflects the degree of intra-flow interference between the links which use the same channel along the path) and the neighbour interference (which represents the channel time cost to nodes close to the path) into account.

2.3 Non-link Quality Based Routing Metrics

The routing metrics that are not extended from ETX are considered as non-link quality based in this work. The other routing metrics design may take network parameters (such as energy, throughput, delay, channel usage etc.) rather than link quality into their metrics design. In this section, the conventional routing metric (Hop Count), minimum impact routing (MIR) [52] and capacity-based routing (CBR) [53] are presented.

2.3.1 Hop Count

Traditional wireless ad hoc routing protocols, such as DSDV, AODV and DSR, use hop count as their routing metrics. This is the simplest routing metric as the metric only considers whether a link exists or not. The route is selected based on the smallest number of hops along the path. Therefore, it can be easily computed and the hop count minimised from the source to the destination once the topology is identified. Such a simple algorithm can react quicker than other routing metrics in rapidly changing topologies. Another advantage of hop count is the isotonicity and monotonicity, so that using an efficient algorithm (Bellman-Ford or Dijkstra's algorithm) can find loop-free and optimum paths with minimum total cost. In the following, we use mathematic functions to illustrate the meaning of isotonicity and monotonicity for routing metrics.

We model our wireless ad hoc network as a directed graph $G = (V, L)$ which consists of a non-empty and finite set V of nodes and a set of links $L \subseteq \{<u, v> \mid u, v \in V$ and $u \neq v\}$ with a number of $|V|$ nodes and $|L|$ links. $<u, v>$ indicates a link from node u to node v. $P(S, D)$ represents a path from node S to node D. $W(P(S, D))$ indicates the accumulated link weight/cost from source node S to destination node D. We use algebraic equations incorporating a quadruplet (**P**, $\oplus$, W, $\leq$) to represent the mathematical meaning of a routing metric, where **P** is the set of end-to-end paths and $\oplus$ illustrates the path concatenation operation. E.g, if path a is connected in series with path b, it can also be indicated as path a is concatenated with path b as $a \oplus b$. W is a function to map a path to an accumulated weight, $\leq$ indicates an order relation. E.g. $W(P_1) \leq W(P_2)$ means that the total weight of using P_1 is smaller than the weight of using P_2.

Using mathematical equations, a routing metric is considered to be isotonic if it satisfies the following conditions:

$$W(a) \leq W(b) \rightarrow W(a \oplus c) \leq W(b \oplus c) \quad \textbf{(2.15)}$$

$$W(a) \leq W(b) \rightarrow W(c' \oplus a) \leq W(c' \oplus b) \quad \textbf{(2.16)}$$

Where all $a, b, c, c' \in$ **P**. These two equations (2.15) and (2.16) state that the order relation between the weights of any two paths is preserved if both of them are appended (posterior connected) or prefixed (prior connected) by a common third path respectively. An example of isotonicity is shown in Figure 2-2. As shown in the figure (bottom left graph), if $W(a) \leq W(b)$, $W(a \oplus c) \leq W(b \oplus c)$ proves that it is isotonic as the order relation is not changed when a posterior common third path is added. The graph located in the bottom right of Figure 2-2 also illustrates the isotonicity as the order relation remains unchanged when these two paths (a and b) are proceeded by another predecessor common third path as $W(c' \oplus a) \leq W(c' \oplus b)$. In general, a routing metric is considered to be isotonic if the predecessor (or posterior) links weight is not changed due to the subsequent (or prior) link choices; otherwise, a routing metric is not isotonic if the predecessor (or posterior) links weight can be affected by the subsequent (or prior) link choices.

A routing metric is considered to be monotonic if it satisfies the following conditions:

$$W(a) \le W(a \oplus b) \tag{2.17}$$

$$W(a) \le W(c \oplus a) \tag{2.18}$$

Where all *a, b, c* $\in$ **P**. Here, monotonicity implies the weight of a path does not decrease when prefixed or appended by another path. In other words, non-negative values have to be used to enable the routing metric to be monotonic [54].

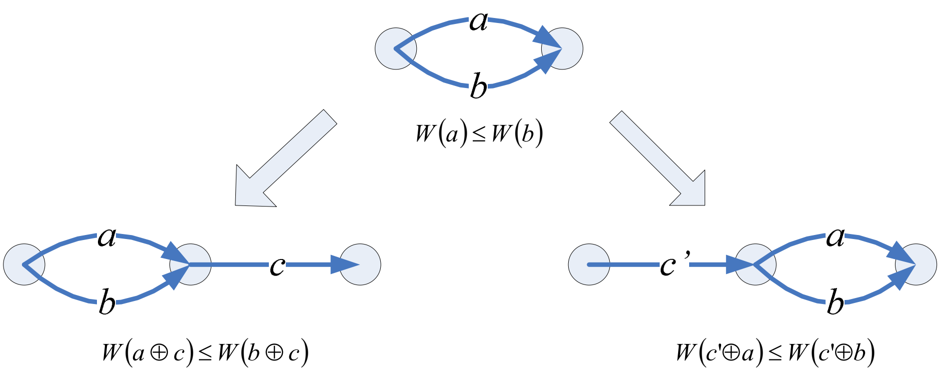


Figure 2-2 An example of isotonicity

Although the simplicity and stability of hop count routing metrics are useful characteristics for wireless ad hoc routing metric design, the metric does not take other factors (e.g. interference, link capacity and channel utilization) into account which may result in a poor performance on route establishment.

2.3.2 Minimum Impact Routing

In wireless ad hoc networks, system capacity is considered interference-limited as only a limited number of users can communicate simultaneously due to interference between transmitting nodes and surrounding nodes sharing the same spectrum. Thus, it is important to consider the interference on the transmitters and receivers in an ad hoc network. Interference information is useful when making higher-layer decisions such as routing. Conventional routing metrics such as hop count fail to take interference into account. In [52], Lu et al. proposed a Minimum Impact Routing (MIR) which selects the route based on the lowest number of disturbed nodes (DN) along the path in order to minimise the interference to other nodes.

Minimum Impact Routing (MIR) aims to minimise the number of disturbed nodes (DNs) for a multi-hop transmission, thereby enhancing the overall spectral efficiency. It selects a route that has the lowest disturbance impact between the source node and destination node. MIR only takes the disturbance (outward) interference into account. Here the link weight of MIR is defined as:

$$w_{ij} = \frac{1}{D_j}, \forall i, j \in V \tag{2.19}$$

Where D_j is the disturbance level which is the number of disturbed nodes of node j. The Minimum Impact Routing metric picks the path with the lowest cost of accumulated disturbed nodes from s to d in the network T.

Although MIR aims to reduce the overall interference by minimizing the number of end-to-end disturbed nodes along the path, it fails to account for the fact that practical interference is based on the disturbed transmitter power, path loss, etc. In addition, MIR encourages traffic flow through less congested areas which results in creating longer paths and increases the relaying burden in the network.

2.3.3 Capacity-based Routing

In [53], Liu et al. proposed a cognitive routing metric design called Capacity-based Routing (CBR) which takes varying link capacity into account in order to improve the capacity of wireless ad hoc networks by selecting nodes/links with higher capacity. It also aims to reduce the overall interference level by shifting traffic to the edge of the network where there is less interference. However, CBR is not considered as cognitive routing (see page 25) as it only observes and utilises node capacity without the technique of reasoning and an acting process to improve network capacity. Although it can improve network capacity when network traffic load is low by shifting the path to the edge of the network, it cannot maintain network capacity when more traffic arrives as it will generate more relaying hops to avoid congestion areas. The unstable route selection process cannot assist the reinforcement learning based channel assignment scheme on its channel selection (results will be shown in Chapter 7), therefore network capacity is reduced. The link weight of CBR is defined by [53]:

$$w_{ij} = \frac{1}{C_j}, \forall i, j \in V \tag{2.20}$$

where C_j indicates the capacity of node j. By using Dijkstra's algorithm, which is introduced later in this chapter, CBR prefers to select nodes with higher capacities and routes that are established based on the maximisation of the accumulated impact capacity has on an end-to-end basis.

In [53], link capacity is related to the total number of activated links within the interference range of the link as well as the available bandwidth (more details about how the capacity model is defined can be found in Chapter 5). Although CBR can cognitively take the varying link capacity which reflects the traffic pattern and interference into account, the lack of selecting the shortest path can even increase the interference under medium or high traffic load networks.

2.3.4 PARMA

In [55], Zhao et al. proposed a PHY/MAC aware routing metric for wireless ad hoc networks (PARMA) which takes into account factors including physical-layer link speed and MAC-layer channel congestion. It aims to minimize the end-to-end delay that includes both transmission and access times by comparison with traditional minimum hop count routing metric. Although the routing metric uses cross-layer information to avoid those links with low data rate and high retransmission rate due to the busy medium, it does not take path stability and path length into the metric design. These two factors are important for routing metric design as dynamic routing (low path stability) provides inefficient channel assignment which reduces the efficiency of MAC schemes, and longer paths indicate a higher relaying burden which requires more bandwidth to accommodate extra relaying traffic. Finally, end-to-end delay can be improved by using PARMA under low traffic conditions, but networks are easily saturated due to the insufficient network capacity under high traffic demands.

2.4 Routing Metric Design

Although the research work on routing metric designs is increasing, there is no consensus solution for wireless ad hoc routing metrics. In addition, there is a trend for metrics that are increasingly complicated taking into account multiple link/network factors in order to improve routing performance. Therefore, in this thesis, we aim to design a simple wireless ad hoc routing metric that not only can account for channel diversity in a multichannel environment, but can also react back to the distributed channel assignment scheme to make the future channel selection in a more efficient way. Although aforementioned WCETT [28] and MIC [45] have awareness of channel diversity, their route establishment have no impact on the channel assignment scheme. Moreover, their route establishment may consume even more radio resources due to the unawareness of path length and route stability. Chapter 7 proposes a cognitive routing metric design (CGB) which uses channel utilization level to build routes and it also provides an efficient channel selection process for a reinforcement learning based channel assignment scheme (results are shown in Chapter 8). This cognitive routing is performed firstly by monitoring and perceiving current network conditions including interference, channel utilization, load balancing and relaying burden impact; then planning, deciding and acting on those conditions, learning from the consequences of its actions, and finally through learning a routing decision can be made in order to achieve end-to-end goals.

2.5 Routing Protocols

In Chapter 1, we listed several traditional wireless ad hoc routing protocols including proactive routing protocols (DSDV and WRP), reactive routing protocols (AODV and DSR) and hybrid routing protocols (ZRP). The advantages and disadvantages of each type of routing protocol were also pointed out. Due to the scope of the thesis which is to design cognitive routing metrics that can take into account environmental factors in the link weight function instead of traditional hop count in order to minimize relaying impact on the network while still maintaining network capacity, throughput and delay under different traffic load conditions, only a few routing protocols are discussed in the thesis for the purpose of understanding the integrated wireless ad hoc routing process as a whole.

2.5.1 Proactive Routing Protocol – DSDV

Amongst proactive (table-driven) routing protocols, Destination-Sequenced Distance Vector (DSDV) protocol is one of the most famous and the earliest routing protocols, and was presented by C. Perkins and P.Bhagwat in 1994 [17]. It applies a modified version of the Distributed Bellman-Ford algorithm (DBF) [56, 57] to solve the poor looping properties (count to infinity) caused by incorrect route information (broken links). DSDV is proposed to solve these route looping problems by introducing a frequent dynamic update on detecting topology changes. This is achieved by each node periodically broadcasting routing updates in order to obtain updated information on the network topology. The routing update is tagged with a sequence number which can distinguish stale or incorrect routes from recent ones. A route is considered to be preferred if its sequence number is greater than the others. To maintain consistency of route information under frequent changes of topology, each node transmits its routing table packets periodically and incrementally once topological changes are detected. Update information from each node consists of the target destination's address, number of hops required to reach the destination and its new sequence number regarding that destination. If the same sequence number occurs among different paths, the smallest metric will be selected to forward packets. With the periodic routing information updates and newest sequence number, each node can obtain the correct shortest path to each other node quickly regardless of the topology changes which can result in stale or incorrect route information.

There are two types of update packets used to reduce routing overhead: "full dumped" which carries all the available routing information and "incremental" which carries only information which differs from the last full dump. Although these two types of update are introduced to reduce routing information, DSDV still generates a large amount of routing overhead due to the requirement of periodic routing messages, especially within a large network. Therefore, network bandwidth is wasted by exchanging these frequent routing messages among all nodes even when the network is idle.

2.5.2 Reactive Routing Protocols – DSR and AODV

In order to reduce unnecessary bandwidth waste caused by routing overheads in proactive routing protocols especially when the network is idle, reactive routing protocols are often proposed which only send out route request packets when a node has packets to send [14, 16]. This means routes are only determined on demand rather than maintained all the time by the continuous periodic updating in proactive protocols.

Generally, reactive routing protocols can be further classified into two categories: source routing and hop-by-hop routing [16]. In source routing, each data packet contains the complete source to destination route whereas a node only needs to know the source and destination as well as next hop routing information in hop-by-hop routing. One of the best known reactive protocols which uses source routing is Dynamic Source Routing (DSR) [22], which is composed of two mechanisms: route discovery and route maintenance. Route discovery is used only when a node has packets to send to a destination and does not already know a route to the destination. To initiate route discovery, route request messages of the original source node are flooded into the network in a controlled manner. Nodes send a route reply back to the original source node with their route records to the destination node if they know a way to the destination or if they are the destination itself. Nodes that receive the route request message and do not know the destination will append their own address to the route record in the request packet and then broadcast the request to their neighbours. In this way, route discovery costs can be limited as each node maintains a cache of routes it has heard. Route maintenance is achieved by acknowledgements and route error messages when a source route is no longer valid due to the change of network topology. The sender can then find an alternative valid route from its route cache or can invoke the route discovery process again to find a new route; route maintenance is only performed when the source node is actually sending packets to the destination.

The main advantage of source routing is that nodes do not need to periodically send beacon messages to their neighbours to inform them of their presence. Another advantage is that intermediate nodes do not need to maintain up-to-date routing information for each activated route as complete routing information is kept in each packet header. The major disadvantage compared with hop-by-hop routing is the routing information overhead grows as the number of intermediate nodes increases along the route [16, 41].

Ad hoc On-Demand Distance Vector (AODV) Routing is one of the best known hop-by-hop reactive routing protocols, and was developed by C. Perkins, E. Belding-Royer and S. Das [21] in order to further reduce routing overhead problems. AODV combines both essential mechanisms of DSDV and DSR. It applies the sequence number and periodic beacons on a hop-by-hop basis from the DSDV mechanism, as well as the on-demand route discovery process from DSR. Unlike DSR, when route request packets accumulate route information through each intermediate node along the path, the request packet of AODV only contains the source and destination as well as the next hop; therefore a large amount of routing information can be reduced by using AODV due to the hop-by-hop basis. Also due to the hop-by-hop basis, HELLO packets are required to be sent locally and periodically to maintain connectivity among the neighbourhoods, similar to the routing table update of DSDV. Moreover, AODV also applies the sequence number of DSDV in order to avoid loop and count-to-infinity problems as well as avoiding stale routing information caused by link breakages. The main advantage of using AODV over DSR is that it is more adaptable in relatively large and dynamic networks.

To sum up, DSR is better for use in a small and stable network as the route cache of each node contains multiple valid routes; therefore if a source node finds a valid route in its route cache, it does not need to initiate a route discovery process which saves network bandwidth for flooding. In contrast, AODV can cope better than DSR in a relatively large and dynamic network as it uses better up-to-date paths due to its sequence number.

2.5.3 Applicable Routing Protocols

In this thesis, we examine routing metrics in a static wireless ad hoc network without node movement and we assume no link or node failure takes place. Since the traditional routing algorithm/metric is the hop count, which results in a fixed value for each link weight if the network topology is stable and the links are reliable, once a source node obtains a route to a destination, this route will always be valid and with minimum cost under those assumptions and conditions. In this way, Route Request packets will not be flooded for routes that have been utilized before; thus, routing messages are reduced and network bandwidth is saved. Therefore applying a reactive routing protocol seems to be a wise option for a relatively stable network topology.

However, in this thesis, we are trying to examine different routing metrics by taking 'cognition' which includes network environment factors (such as interference, load balancing, link capacity, throughput, channel assignment) into account rather than a simple hop account; hence, cost/weight value of each link may differ every time a new source traffic is activated as those metrics are likely to be affected by traffic flows even with a stable network topology. In this way, a new shortest path is always requested as the previous one may no longer be valid due to the highly dynamic changing feature on routing metrics. The reactive routing protocol is not suitable for this type of routing metric design as the excessive flooding due to the frequent route requests increases the amount of routing overheads and reduces network bandwidth. Therefore, a proactive routing protocol is used to evaluate the cognitive routing metric designs proposed in this thesis.

2.6 Dijkstra's Algorithm for Shortest Path

In this thesis, Dijkstra's algorithm [58] is selected to solve the shortest path problem for a given graph with link weight/cost values, for all routing metrics. The functionality of Dijkstra's original algorithm can be extended for various purposes. For example, the OSPF (open shortest path first) protocol is an implementation of Dijkstra's algorithm for Internet routing [58]. Dijkstra's algorithm can effectively select the route with the lowest accumulated cost. In order to achieve higher level goals in the system, we can exploit the optimization function of Dijkstra's algorithm by redefining the cost. That is to say, the definition of cost is manipulated in order to serve a different purpose [53].

Consider a directed graph $G = (V, L)$ which consists of a non-empty and finite set V of nodes and a set of links $L \subseteq \{<u, v> \mid u, v \in V \text{ and } u \neq v\}$ with a number of $|V|$ nodes and $|L|$ links. $<u,v>$ and $w_{u,v}$ indicates a link from node u to its adjacent node v and the cost respectively. Dijkstra's algorithm keeps two sets of vertices. One is the set of vertices whose shortest path from the source have already been determined (we call it the visited set, S). The other one is the set with remaining vertices (we call it the unvisited set, V-S). Let d denotes the shortest cost from the source vertex to the current vertex. Given a path π in G determined by the Dijkstra's algorithm. $p(v)$ denotes the Predecessor of v for any v in π ($v \neq s$). The following execution steps show how to find a shortest path by using Dijkstra's algorithm from source node s to destination node x:

Initial Stage:

1. Set S to empty
2. Set $p(v)$ to empty
3. Set the cost from source vertex to other vertices to be infinity, $d(s,v) = \infty$
4. Set the cost from source to itself to be 0, $d(s,s) = 0$

This initial stage sets up the graph so that each node has no predecessor and the estimates of the distance of each vertex from the source are infinity, except for the source itself.

Repeat Stage:

1. Find the vertex (u) from the unvisited set (V-S) that gives the shortest distance to the source
2. Process the vertices (v) still in V-S connected to u and check whether the current best estimate of shortest distance to v can be improved by going through u: If $d(s,v) > d(s,u) + w_{u,v}$, then $d(s,v) = d(s,u) + w_{u,v}$ and let $p(v) = u$.
3. Take node u as visited. i.e. $S = S \cup \{u\}$,
4. If $u = x$, the Dijkstra's algorithm process terminates as the shortest path has been discovered from the source s to the destination x, otherwise return to the first step of the repeat stage.

The other well known algorithm that is often used to find the shortest paths in a network is Bellman-Ford. Although Bellman-Ford can work with negative cost where Dijkstra's algorithm cannot, it is slower to find the shortest paths than Dijkstra's algorithm since it relaxes all edges by $|V|-1$ times rather than greedily selects the unvisited minimum cost node. Conventional routing algorithms normally find the shortest path route with minimum hop count to improve efficiency [28]. However, in a wireless ad hoc network, the minimum hop count is not necessarily the best solution. First of all, the diverse capacity levels due to different link length, spectrum availability and/or power level can be used more efficiently if the cognitive routing metric design takes them into account.

2.7 Conclusion

In this chapter, the relevant background information of this research work has been provided. Initially, three main types of wireless ad hoc routing protocol are shown with detailed examples, and the reason for using proactive routing protocol for this research work is also given. This is followed by a literature review on wireless ad hoc routing metric design with a detailed discussion on the limitations and merits of those existing routing metrics. Dijkstra's algorithm is described as a method to find the shortest path. Finally, cognitive radio and cognitive network have been introduced to illustrate the concept of cognitive routing.

Chapter 3

3 Modelling Techniques and Verification Methodology

Contents

3.1 Introduction

The purpose of this chapter is to present the wireless ad hoc routing evaluation methods utilized throughout this thesis before introducing the main research work. There are different approaches for engineers to conduct their research. Each approach has its merits and flaws for varying types of research work. Computer simulation is one of most widely used and efficient methods for communications researchers. Robert E. Shannon defines simulation as the process of designing a model of a real system and conducting experiments with this model for the purpose of understanding the behaviour of the system and evaluating various strategies for the operation of the system [59]. Researchers can use the technique to imitate some real particular systems or to implement system scenarios that are not possible in the real world. Therefore, the advantages of selecting simulation as the main method of evaluation are due to the characteristic of low cost and the feature of flexibility. With the growing complexity of wireless communications architecture and scenarios, analytical models are expensive and sometimes impossible to implement, whereas the scenario configurations of simulation models can be easily adjusted and results can be reproduced as needed. In addition, thanks to the development of computing technology, powerful computers and sophisticated simulation software are available to allow a more accurate behaviour modelling of wireless communications. Moreover, it is extremely difficult to effectively model the behaviour of networks and systems with analytical models since modern network architectures are quite complicated; and the main intention of this research was to design a novel technique to associate a cognitive routing metric with a distributed channel assignment scheme in wireless ad hoc networks, in order to reduce network relaying hops while still maintain network capacities. Therefore, simulation has been chosen as the main approach to conduct the works in this thesis.

This chapter firstly describes the details of the Monte Carlo simulation technique. In the following section, the introduction of the simulation tool MATLAB is presented in comparison with other widely used simulation tools and languages. Next, the parameters used to evaluate the network performance are shown and a validation method is discussed. The chapter ends with a brief conclusion.

3.2 Simulation Tools

Nowadays, there are many simulation programming tools available to perform simulations in communication engineering research. Although many programming tools are capable of conducting simulations in communications research, each one has its unique features that can achieve certain needs of research easier than the others as well as its limitations. E.g. C programming has the advantage on the speed of run-time due to its straight-forward compiled rather than interpreted language so the machine instructions can be executed more efficiently, but as the mother of modern languages [60], it needs more programming to achieve the functions of other programming tools, for example, it requires more external programmed loops to solve matrix problems whereas these can be solved easily in MATLAB, as will be discussed in more detail later. OPNET and NS2 are popular network simulators for communication research as they have many built-in simulation models, which include many standard communication protocols across different layers for designers to test new networking protocols or to modify the existing protocols using packet-level analysis. The disadvantages of these network simulators are that the simulations require more processing power and time due to the radio pipeline stage, especially in the case of OPNET as it is designed for cable/wire networks. Therefore with radio networks 'virtual wires' are effectively generated to provide connectivity, with packets being duplicated from the source to each node, even if only interference is being calculated. Each of these packets then goes through a *12* stage receiver pipeline. Moreover, as the purpose of this thesis is to reduce relaying hops while maintaining network capacity by designing cognitive routing metrics with reinforcement learning based channel assignment scheme, the efficient modelling of mutual interference is critical, and MATLAB and C can be custom designed to model this efficiently. In addition, the simulation analysis is mainly focused on the link/flow based transmissions rather than the packet based transmissions. Regarding the reinforcement learning based channel assignment scheme (details can be found in Chapter 7 and 8), links will have a preferred channel or channels after a period time of learning process. In order to process the channel weight of links in a more efficient way, MATLAB is selected as it has better computational flexibility than the others.

MATLAB is the abbreviation for Matrix Laboratory developed by MATHWORKS Inc [61]. In addition to those highlighted above, there are several other advantages of using MATLAB rather than other high-level programming languages for this research work. Since it is an interpreted language for numerical computation, it can compute numerical calculations such as array, matrix and cell, and is reasonably efficient without the need for complicated programming. In addition, there are many built-in or predefined functions and varying toolboxes for users to perform different kinds of simulations in a more efficient way. For example, one of the functions, "*graphshortestpath* [62]" which is a built-in function from the Bioinformatics toolbox, is frequently used in this thesis. It has the ability to solve the shortest path problem using graphs and it can return values including every node on the path and the path cost. The function is shown below.

$$[dist, path, pred] = graphshortestpath(G, S, T) \tag{3.1}$$

Where *dist* is the path cost value; *path* contains every node along the path; and *pred* contains the predecessor nodes of the path. *G* is the *N-by-N* sparse matrix which contains the cost/weight of each link/edge. *S* and *T* are the source node and destination node respectively. Figure 3-1 Example of using "*graphshortestpath*" to find the shortest path in a directed graphshows an example of using "*graphshortestpath*" function to find the shortest path from node 1 to node 4, and the content of links with the cost from G is shown in Table 3-1.

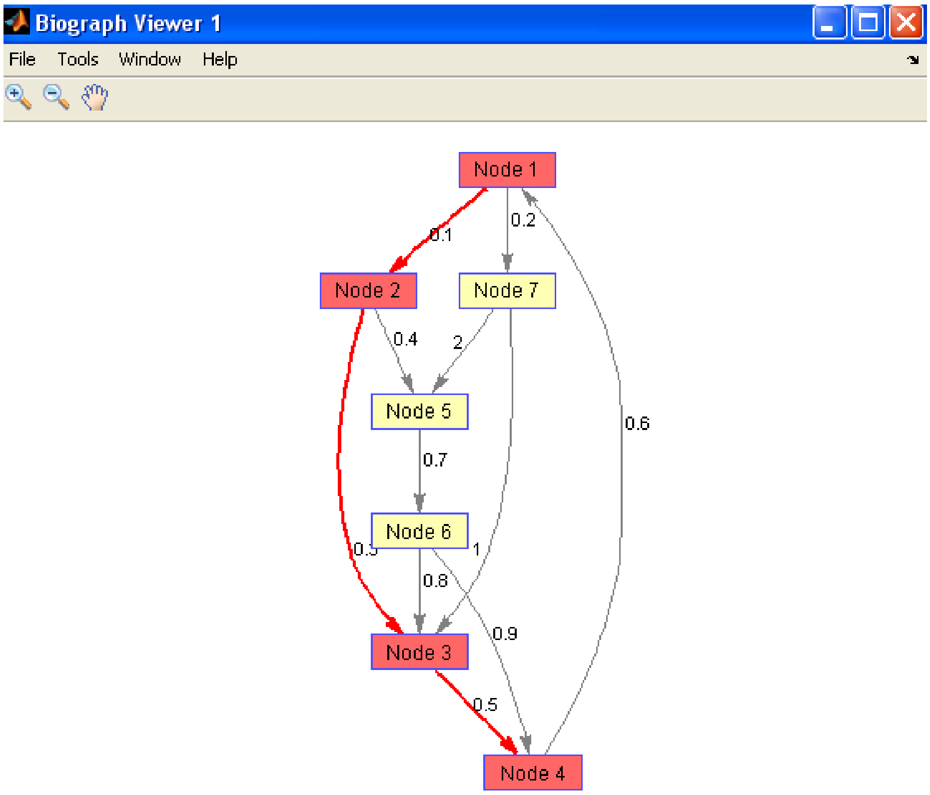


Figure 3-1 Example of using "*graphshortestpath*" to find the shortest path in a directed graph

(4,1)	*0.6000*
(1,2)	*0.1000*
(2,3)	*0.3000*
(6,3)	*0.8000*
(7,3)	*1.0000*
(3,4)	*0.5000*
(6,4)	*0.9000*
(2,5)	*0.4000*
(7,5)	*2.0000*
(5,6)	*0.7000*
(1,7)	*0.2000*

Table 3-1 Links with the cost value for *G*, N-by-N sparse matrix– one of the inputs for the "*graphshortestpath*" function

As can be seen from the example, *dist* is *0.9* and *path* returns *[1 2 3 4]* as the shortest path which relays through node *2* and *3*. This single syntax provides a shortest path and its cost value as well as the graphical result by using the built-in function from the Bioinformatics toolbox. These built-in functions allow users to produce code efficiently. Moreover, it offers a friendly interface for users to trace any errors and debug easily due to its interactive programming feature. MATLAB is selected as the main simulation tool for our research work, despite its slower execution, as we consider the simulation development speed is more important than the simulation speed. Simulation can take a long time, but can run without user intervention (during a day or overnight). MATLAB has been used to capture the features of each routing metric design in wireless ad hoc networks and the simulation procedures are illustrated in Figure 3-2.

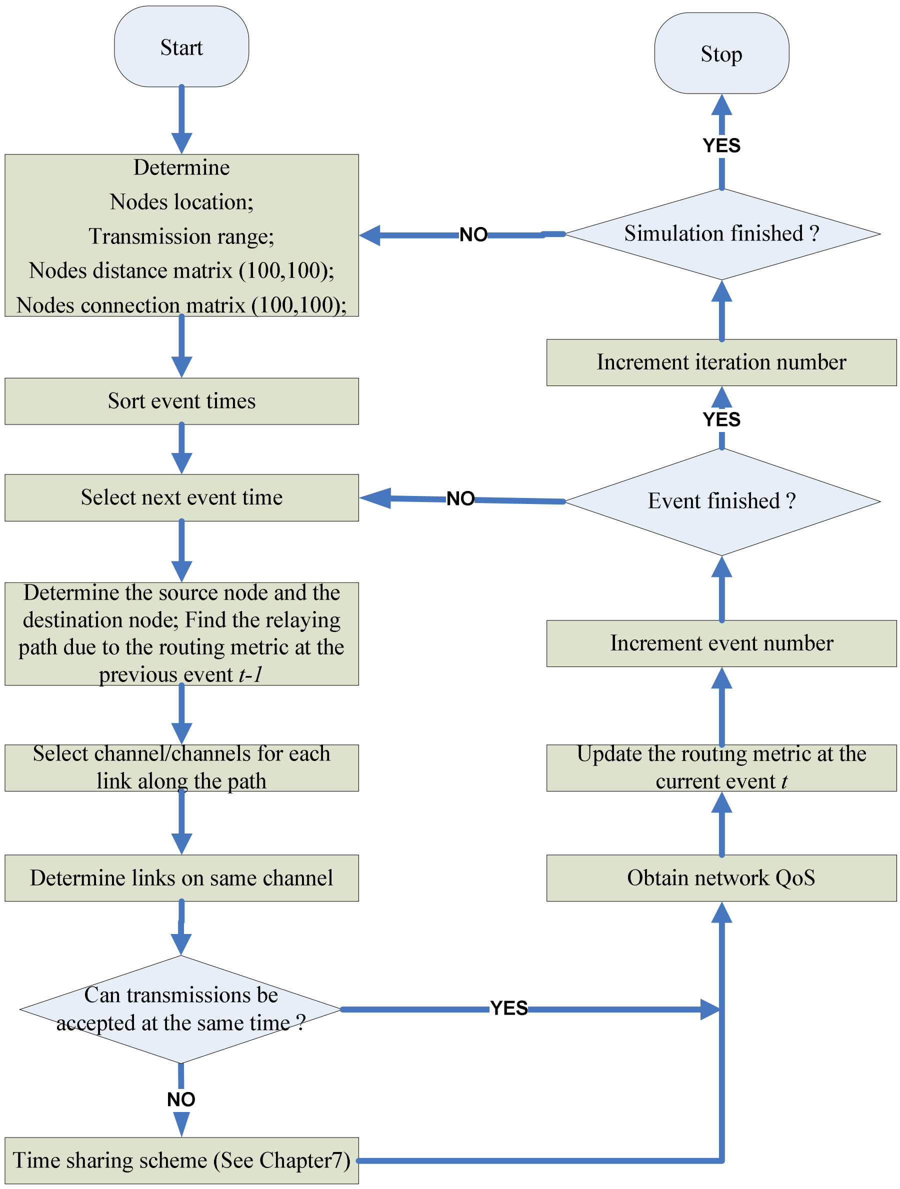


Figure 3-2 Flowchart of simulation procedure

3.3 Monte Carlo Simulation

The impact of applying different types of routing metric in wireless ad hoc networks is studied in this thesis by using the Monte Carlo simulation technique. Monte Carlo simulation is a classic computational algorithm for communication engineers. It relies on repeated random sampling to generate statistical results and determine the behaviour of the system. A large number of sets are provided to perform the simulation in order to reduce the effect of random fluctuations enabling the statistical certainty of the result to become more precise [63].

There are three different types of wireless ad hoc network scenario used in this thesis. We consider nodes have no mobility throughout the thesis. One implements homogeneous nodes in random distributed locations and varying sink nodes are selected as shown in Figure 3-3. This scenario is applied in Chapter 4 to understand the challenges of routing metric design in wireless ad hoc networks. Another one is the heterogeneous scenario with different types of node located in a grid network. Aggregation nodes (with higher capacity than normal nodes) are randomly distributed in the middle of the network and landmark nodes (with highest capacity) are implemented on both edges of the network as shown in Figure 3-4. This scenario is used in Chapter 5 to investigate the bottleneck node problem of wireless ad hoc networks. The last scenario uses homogenous node types with random locations through the network and a common sink node is selected in the middle of the network as shown in Figure 3-5. This is similar to a battlefield scenario where the headquarters receives/sends the messages from/to the army nearby. The scenario is applied in Chapters 6, 7 and 8 to improve the network QoS, capacity, bottleneck problems of wireless ad hoc networks by varying routing metric designs.

The reason of using two network scenarios for random node placements with dimensions of *40* km and *550* meters respectively is as follows. The early scenario (40×40 km^2) is focused on designing and investigating how link weight can be manipulated by extending the metric design of MIR [52]. In [52], varying radio link length is adopted in three different topologies: hexagon, square and chain. In order to further analyse how well MIR can route traffics around dense areas in a random topology, the number of *100* nodes with network dimension of *40* km is selected. The network connectivity is also tested with varying radio link lengths under this network scenario by using the analytical expression in [64]. Later in the thesis we implement our routing metric with a reinforcement learning based channel assignment scheme in a more practical network scenario, including path loss, SINR, channel bandwidth, etc. Therefore, in order to build a fully connected network with high probability under a environment where *100* random nodes and transmission range of *100* meters are required, the network dimension is selected to be *550* meters by using the analytical expression in [64]. Furthermore, the network size can be modified to the same standard if the transmission range is carefully adjusted to provide a fully connected network. Using different scenarios can help us to understand routing metric design impact under a wide variety of wireless ad hoc network applications.

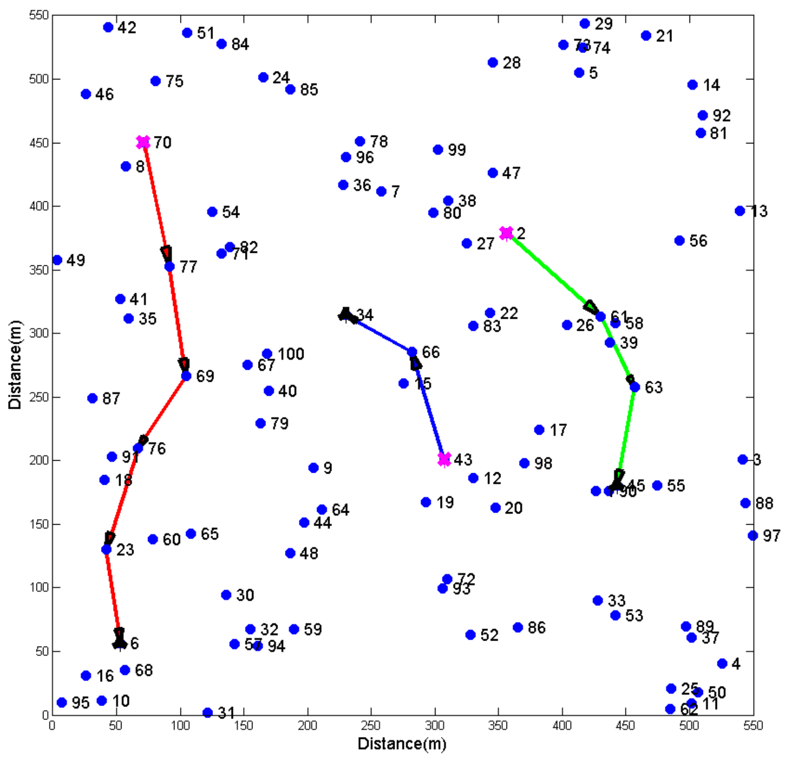


Figure 3-3 Example of scenario 1: homogeneous type with multiple source/sink nodes randomly distributed in the network produced by MATLAB

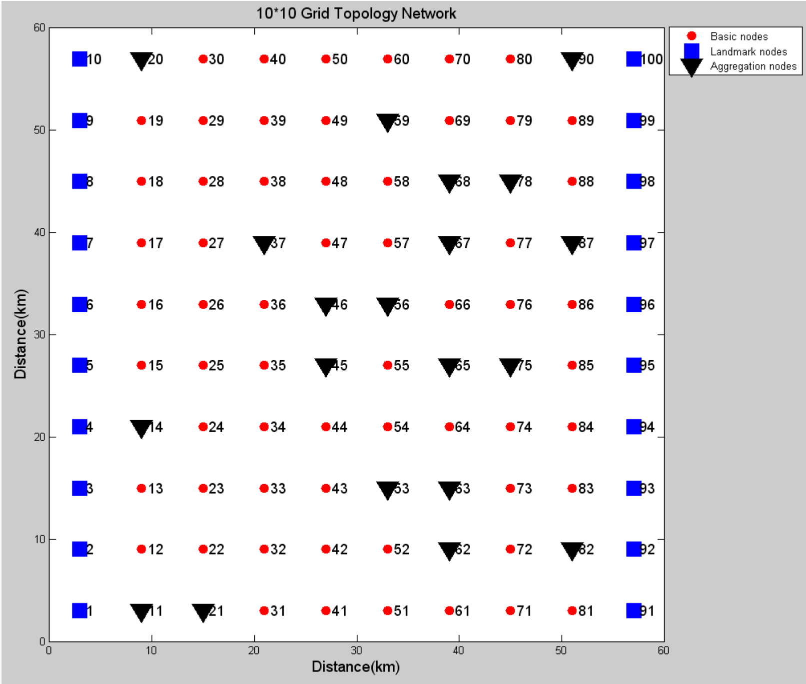


Figure 3-4 Example of scenario 2: heterogeneous type with multiple source/sink nodes located in a grid network produced by MATLAB

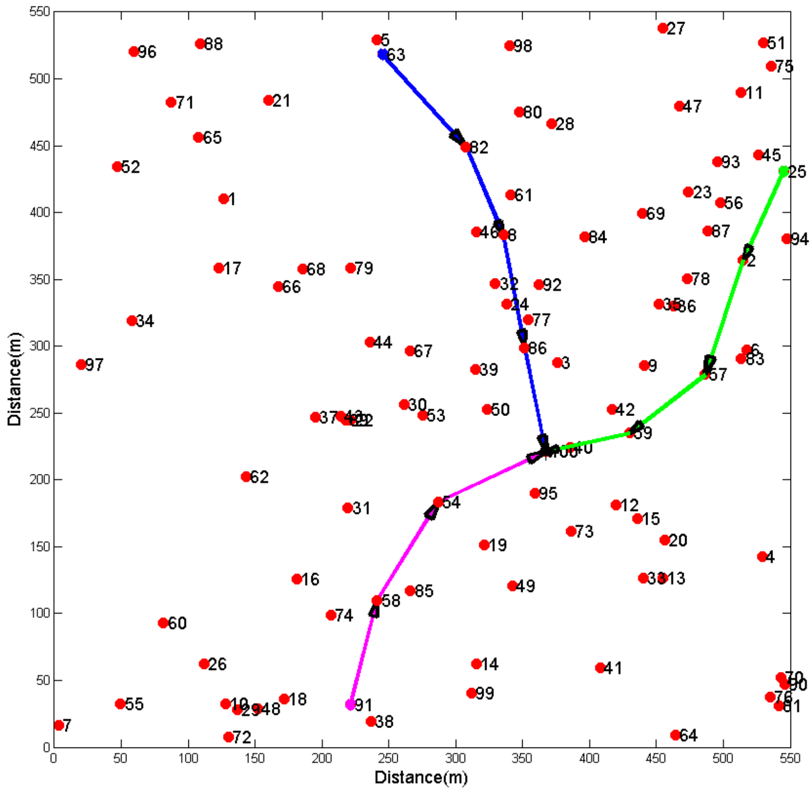


Figure 3-5 Example of scenario 3: homogeneous type with a common sink located randomly in the network produced by MATLAB

3.4 Validation of Results

Performance analysis of wireless ad hoc networks is very challenging due to the facts that such analysis must to take into account the network topology, radio propagation, multiple access, routing, traffic patterns, etc. In this section, we will apply two methods to validate our simulation result. Firstly, possible analytical approaches are discussed, such as capacity analysis in wireless ad hoc networks, to provide a performance comparison with our simulation framework in Chapter 7 and 8. Secondly, our early simulation framework (in Chapter 4) of using MATLAB is compared with a previously published result [52] from an independently-written simulator (OPNET).

3.4.1 Validation Using Analytical Results

Several studies have focused on finding the maximum achievable capacity on a per-node basis. E.g. in [12], it is shown that each node can obtain $\Theta(W / \sqrt{n \log n})$ bits per second. In [30], the authors examined the dependence of per-node capacity on 802.11 MAC interactions and traffic patterns for various simple network topologies, such as a single cell, chain, uniform lattice and random network.

Here, we will examine wireless ad hoc network throughput on a per-flow basis by considering current traffic flows and present an analytical model that takes into account network size, traffic flows, radio range and maximum transmission rate. Our simulation framework is verified by comparing with the analytical results and the similarities and differences between the two are discussed.

Consider a network with n identical randomly located nodes (no mobility) within a square area of A, each node is capable of transmitting at W bits per second over a common channel and a perfect scheduling algorithm, which knows the locations of all nodes and all traffic demands, is applied. Then transmissions can be coordinated temporally and spatially to avoid collisions. If such perfect information is not available, the throughput is smaller.

Let L denote the expected distance that a packet traverses from a source node to a destination node and r the common range of all transmissions. Then, the expected number of hops taken by packets is no less than $\frac{L}{r}$ in a connected network [12]. If the number of traffic flows is known as λ, therefore the expected number of activated links is no less than $\frac{L}{r}\lambda$. We can obtain the lower bound end-to-end throughput of a traffic flow if no spatial reuse is considered here. In other words, all transmissions interfere with each other, so they can only obtain one portion of the channel for its transmission which is W divided by the number of activated links under the perfect scheduling approach. For shortest path routing metric which generates minimum number of hops amongst all routing metrics, the expected end-to-end throughput of a path is approximately $\frac{Wr}{L\lambda}$.

The analysis of no spatial reuse is a worst case scenario as no transmissions can occur simultaneously. However, transmissions that are far away can occur simultaneously, provided there is no excessive interference on both sides. This spatial concurrency and frequency reuse can intuitively increase the end-to-end throughput of a traffic flow.

In Chapter 7 and 8, the common destination is selected at the centre of the network. Therefore, we can estimate the expected path length (L) of using shortest path routing metric for a random traffic pattern, which is $\frac{2\sqrt{A}}{3}$ (more details about this can be found in Chapter 7). Due to the aforementioned equations, we can deduce the end-to-end throughput by using shortest path routing metric in terms of transmission capability, transmission range, traffic flows and network size:

$$C = \frac{3rW}{2\lambda\sqrt{A}} \tag{3.2}$$

Considering the throughput analysis on a per-flow basis, the minimum number of traffic flows is 1. Therefore, we can obtain the end-to-end throughput of one traffic flow as

$\frac{Wr}{L}$. For the scenario where a common destination is selected at the centre of the network, the end-to-end throughput on a path is:

$$C = \frac{3rW}{2\sqrt{A}} \tag{3.3}$$

In Figure 3-6, analytical and simulation results are presented for the end-to-end throughput analysis. The simulation result is obtained in a single channel environment with a network dimension of *550* meters. The transmission range of nodes is *100* meters and the destination node is selected at the centre of the network. The maximum channel capacity is *9* Mbps. No spatial concurrency is considered in the simulation as each link competes for the channel capacity with all the others. The end-to-end throughput of analytical and simulation results follows an exponential drop with increasing the level of traffic load. It is observed that the simulation results agree closely with the theoretical values.

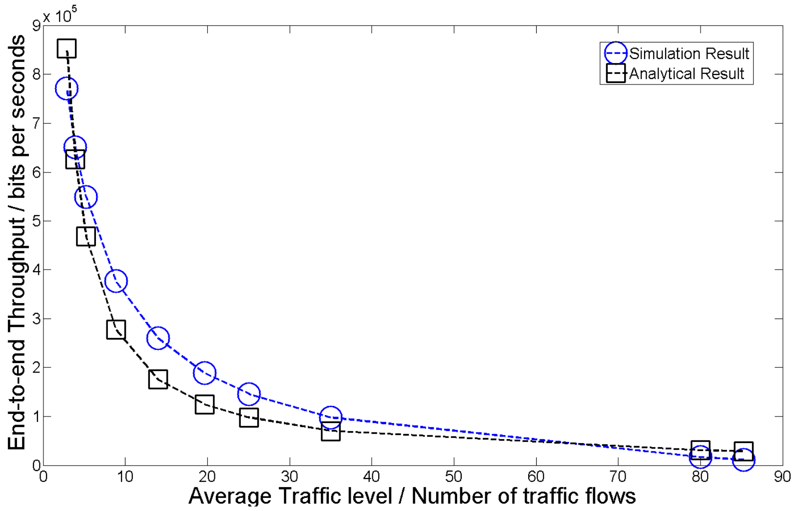


Figure 3-6 Analytical result against simulation result

3.4.2 Validation Using OPNET

Chapter 4 presents our early simulation work using MATLAB to reduce traffic congestion in the dense area by routing traffic through the edge of the network. This is done by a routing metric design, Minimum Impact Routing (MIR) which selects routes based on the lowest number of disturbed nodes (DNs) along the path. More details of this routing metric can be found in Chapter 4 and [52]. Here, we will validate our simulation results by using MATLAB, compared with the results obtained by using OPNET in [52]. The network parameters used here are the same as in [52], and they are listed in Table 3-2. The interference range is twice the transmission range. The square network topology that is produced by MATLAB is shown in Figure 3-7.

Routing metric	MIR
Network size	*16* x *16* km
Node spacing	*2.5* km
Network topology	Square
Number of nodes	*32*
Radio link length	*3, 6, 9, 12, 15, 18, 21* km
Route selection criteria	Minimum number of DNs

Table 3-2 Simulation configurations

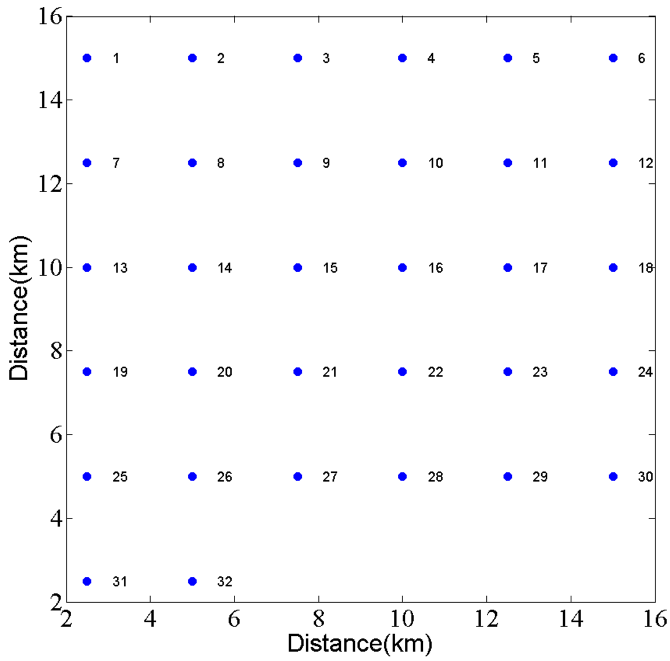


Figure 3-7 Square network topology produced by MATLAB

Figure 3-8 shows the performance in terms of the mean value of the total number of disturbed nodes for all hops along a route against various radio link lengths by using MATLAB, compared with OPNET in [52]. The results of mean DNs along a path are collected through *2000* different source-to-destination pairs and those sources and destinations are selected based on a uniform distribution. As can be seen from this figure, MATLAB obtains similar results in terms of mean DNs as when OPNET is used. MIR has a lower number of DNs when the transmission range increases. This is expected as hop number is decreased when transmission range is increased, and therefore, there are fewer alternative choices of route and the number of DNs is similar. When the link length increases to a link length of *16* km (interference range is *32* km), the node which is located at the centre of the network would expect the mean number of DNs to be *30* (excluding itself and the receiver node) as all nodes are within its interference range.

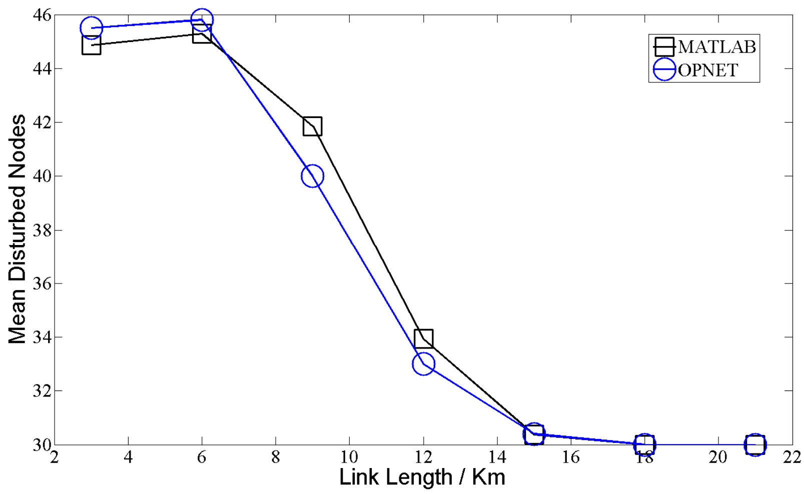


Figure 3-8 Mean value of the total number of disturbed nodes for all hops along a route vs. link length by using MATLAB and OPNET for *32* nodes in square network

3.5 Performance Parameters

Different routing metrics will be presented in the following chapters for optimizing different applications of wireless ad hoc networks. In wireless sensor networks (WSN), energy/power consumption is considered to be more important than other network parameters as sensors are deployed in places where the battery is very difficult or expensive to recharge or replace. In wireless mesh networks (WMNs), quality of service (QoS) is the primary goal rather than energy consumption as it has a relatively stable topology and access points (AP) can be easily replaced or discarded without losing connectivity to the gateway. In mobile ad hoc networks (MANET), maintaining routing information to continuously carry the communication service seems to be the primary challenge due to the mobility of the devices [5]. Although the goals are different, depending on the types of the wireless ad hoc network, the primary target of this research is to design cognitive routing metrics with a distributed channel assignment scheme that can reduce relaying hops while still maintaining network capacity.

3.5.1 Number of Disturbed Nodes and Congestion Levels

The number of disturbed nodes and the congestion level are used initially to help us to understand routing metric behaviour in wireless ad hoc networks. The disturbed node (DN) is defined as a node within the interference range of the node of interest [52]. The congestion level of a node is defined as the total number of activated links within the interference range of the node [53]. More details of the parameters can be found in Chapter 4 and 5. These two parameters can examine the altruistic feature of routing metrics as by taking the disturbed node number into the metric design, traffic can be relayed to the edge of the network rather than through crowded areas such as occurs with DIR routing as shown in Chapter 4. A routing metric that takes other nodes' interest into account when selecting routes is considered to have the altruistic manner; otherwise it is a selfish routing metric if the route is selected based only on the objective node's benefit. These parameters are used in early chapters for the interference model where it is defined as a circle. A more sophisticated model which takes into account SINR, and the distance between transmission pairs and path loss, etc will be applied for the interference model.

3.5.2 End-to-end Bottleneck Capacity

The end-to-end bottleneck capacity is defined as the minimum capacity along the path from source node to destination node including all intermediate nodes. This parameter is important in wireless ad hoc networks as it restricts the network performance. Since communications are carried out on a hop-by-hop basis, a bottleneck node/link can limit the entire performance of a route even if other nodes/links can achieve a better service along the path. For example, if an intermediate node with low capacity has been selected to relay traffic, even though other intermediate nodes along the path have higher capacity, packets will build up in the bottleneck node as it cannot handle the traffic requirement from upstream links due to its smaller capacity. Eventually, delay will increase and throughput will decrease as packets are queued or dropped at the bottleneck. Therefore, a good routing metric design should take into account the end-to-end bottleneck capacity. Related results can be found in Chapter 6.

3.5.3 Throughput and Delay

Low delay and high throughput are the targets of routing metric design in wireless ad hoc networks. In this thesis, we assume that packet processing time and propagation time are negligible, therefore the network delay is mainly affected by channel capacities. A bad routing metric design could increase the relaying burden in the network, thus channel capacity would be influenced by the interference. One way to improve throughput and delay in routing metric design is to minimize the network relaying burden when selecting routes. Another approach is to associate routing metric design with a good channel assignment scheme, so that channels/capacities can be assigned in a more efficient way to improve delay and throughput. Those ideas of cross-layer design will also be presented in this thesis.

3.5.4 Energy Consumption

Our energy model is described in Chapter 7 and the network energy consumption depends on node activation time, number of nodes in each state (transmitting, receiving and idle), and power consumption of each state. Although reducing relaying hops while maintaining network capacity is the main research target for routing metric design, the network energy consumption can also distinguish the capability of each routing metric, on how well they can reduce network energy consumption while maintaining network capacity. A good routing metric or cross-layer design should reduce the number of activated nodes as well as the activation time of nodes. More details and results will be given in Chapter 7.

3.5.5 Time Sharing Probability

In this thesis, we also study the impact of combining the routing metric with a channel assignment scheme for a wireless ad hoc network. If multiple activated links cannot use the same channel simultaneously due to the SINR at the receiver end, we assume those links can share the channel in an equal and efficient approach at different times instead of channel collision (blocking or dropping) taking place. This assumption can help us to concentrate our research on the routing metric design instead of the MAC scheme as our network performance will be mainly affected by varying routing metrics and channel assignment schemes rather than the application of MAC protocol. The time sharing probability at a traffic load t is defined as:

$$T_t = \frac{N_d}{N_T} \tag{3.4}$$

Where N_d is the total number of links that have to share a channel with other links at different times. N_T indicates the total activated link number.

More details of the time sharing scheme will be shown in Chapter 7. The time sharing probability is a key parameter to illustrate how good a channel assignment scheme is as a higher time sharing probability indicates a lower channel capacity is assigned to each sharing link and vice versa.

3.5.6 Channel Weight

In Chapter 7 and 8, we will provide a novel cross-layer design by associating reinforcement learning based channel assignment schemes with an advanced routing metric. In a reinforcement learning based channel assignment scheme, channel weight is rewarded for a good channel selection if the transmission is successful; channel weight is punished if the transmission collides with other transmissions that are using the same channel nearby. The channel weight accumulates a weight value from the beginning of the first simulation event to the end of the simulation. It is a key parameter to show how well the reinforcement learning based channel assignment scheme adapts with varying routing applications. A good cross-layer design combining reinforcement learning based channel assignment with a routing metric should assign suitable channel/channels to links with respect to their geographical locations, in order to solve the hidden node problem as well as improving channel spatial reuse in the network.

3.6 Conclusion

This chapter has outlined the simulation techniques to be used throughout the thesis. Simulation has been selected as the primary research tool and it is carried out by using MATLAB due to its efficient time-saving programming capability and intuitive numerical functions such as array, metric and cell. In addition, results are obtained from the Monte Carlo simulations with a sufficient number of events to avoid random fluctuations in order to determine the behaviour of the system. Numbers of disturbed nodes and congestion levels are used to examine the potential interference a routing metric can provide in the network. Throughput, delay and energy consumption are the important parameters which are used to compare network performance by varying routing metric designs.

Chapter 4

4 Disturbance/Inconvenience Based Routing

Contents

4.1 Introduction

The purpose of this chapter is to present the early work carried out to design a family of routing metrics in order to avoid congested areas in wireless ad hoc networks. The proposed routing metric, disturbance/inconvenience based routing (DIR), is inspired by

Minimum Impact Routing (MIR), which aims to minimise the number of nodes disturbed on a multi-hop transmission path, therefore enhancing the overall spectral efficiency [52]; the details of MIR can be found in Chapter 2. Unlike MIR, which accounts outward interference only, DIR takes both inward and outward interference into account. DIR emphasizes the route selection not only based on an individual node/link perspective but also take the end-to-end goal into account in addition. DIR is considered to be more cognitive than the MIR and Shortest-path routing metric as it can adjust its link weight by a threshold value or adjust the link weight to the power of k to avoid congested areas or bottleneck nodes.

First of all interference is classified to two different types: disturbance and inconvenience. This is followed by the disturbance/inconvenience based routing metrics design: DIR^k (Disturbance/Inconvenience routing to the power of *k*) and DIR_{th} (Disturbance/Inconvenience routing with a threshold value). The results of applying different routing metrics are illustrated. Finally, the conclusions will be given.

4.2 Disturbance and Inconvenience Interference

Two types of interference can be defined in wireless ad hoc networks: ‘Inconvenience’ and ‘Disturbance’ on inward and outward interference respectively. In this chapter, the inconvenience level is defined as the number of nodes that disturb the object node. The disturbance level is defined as the number of nodes within interference range of the node of interest. This is an early interference model which is based on the number of Disturbed Nodes (DN) in order to explore how a routing metric interacts with the environment by adjusting nodes/links weight. A practical interference model is applied in chapter 7 by taking transmit power, distance between transmitter and receiver and propagation model into account.

Figure 1 (a) illustrates a case where a node of interest has been interfered with by another three nodes, therefore its inconvenience level (I = *3*). Disturbance deals with the outward impact a node will have on the environment and others. Figure 1 (b) shows the object node disturbs four nodes within its interference range, the disturbance level (D =

4). Intuitively, it is desirable to minimize inconvenience at the receiver to achieve the maximum goodput. A route with less outward interference (disturbance) is preferred as it takes other nodes into account and consequently improves the overall capacity of the system. If it is not necessary to compromise other aspects, this type of altruistic behaviour should always be encouraged.

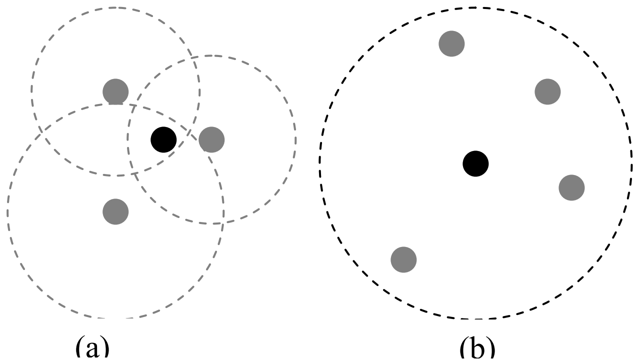


Figure 4-1: Two different types of interference associated with the node of interest shown in black. (a) Inconvenience; (b) Disturbance

The interference/disturbance range (IR) indicates the radius of an area which a transmitting node causes interference/disturbance to the other nodes. In this chapter, it is set to double the size of its transmission range (TR) neglecting any shadowing effects, as investigating the routing metrics is our main concern. Although the discussion of how to identify the disturbed nodes from a node perspective is not the focus of this thesis, one method of how to obtain the number of DNs within the interference range of the node of interest is provided as follows. The location of nodes can be available directly by communicating with a satellite if nodes are equipped with a GPS receiver. In a fully connected network, each node is connected to every other node directly or through relaying. The location of each node can be transmitted to the others by flooding the network with its position. Therefore, each one will be able to calculate its distance to the others. Also, each node can determine the number of DNs within its interference range. The purpose of using the number of DN as the DIR metric design is to explore the route selection behaviour by manipulating link cost rather than implementing this routing metric into a practical interference model. As a more sophisticated interference model will be shown in Chapter 7 and the idea of using the number of DN as a routing metric design can be easily replaced by the interference value suffered in an ILR routing metric design in a more practical sense.

Figure 4-2 shows an example of TR, IR and DN. In this case, there are *12* disturbed nodes within the interference range of the object node.

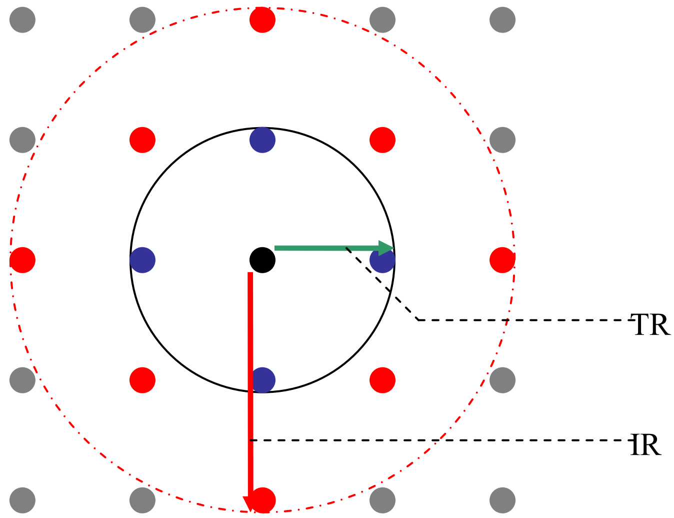


Figure 4-2 Example of Disturbed Nodes (DNs), Transmission Range (TR) and Interference Range (IR)

4.3 Disturbance/Inconvenience Based Routing Metrics

Although the MIR outperforms the shortest path algorithm in terms of reducing interference as it reduces the disturbance along the path, the bottleneck of the system capacity has not been improved dramatically due to the fixed route choice for certain source and destination pairs. In a random network topology, traffic can be jammed by a certain node occupying an important location. In the MIR metric, it cannot solve the bottleneck node problem by shifting the traffic to edges (here we define the 'edge' as locations that are subject to less traffic). This is because MIR only reduces the number of disturbed nodes on a whole path basis, despite a node being selected for delivering the traffic. Therefore, we are going to introduce a family of disturbance/inconvenience based routing metrics (DIR) to minimize the interference level not only for the entire multi-hop transmission path, but also to use fewer nodes for relaying that are subject to less interference, thereby enhancing the capacity of ad hoc networks. In addition, unlike the MIR routing metric design by only taking the outward interference into account, our disturbance/inconvenience based routing metric design takes both inward and outward interference into account.

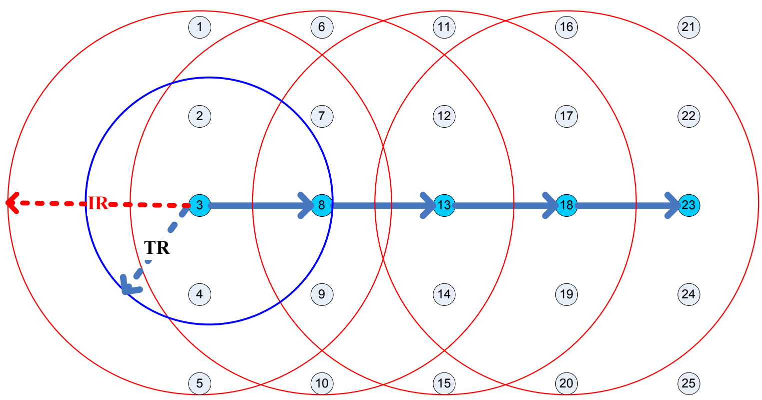
4.3.1 DIR Link Weight Equation

Here the link weight of original disturbance/inconvenience based routing metric is defined as:

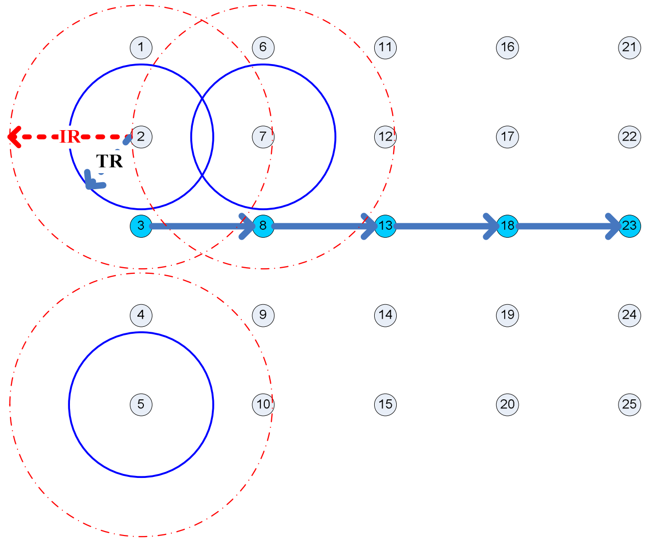
$$w_{ij} = \alpha I_j + (1-\alpha) D_j, \forall i, j \in V, 0 \le \alpha \le 1 \tag{4.1}$$

where I_j and D_j are the inconvenience and disturbance levels respectively for node *j*. 'α' is the interference priority factor. With the value of 'α' approaching *1*, the inconvenience interference will play a major part in the link weight (more selfish). If the interference priority factor is close to *0*, disturbance interference dominates the weight, therefore the metric is considered to be more altruistic. In the case where 'α' is equal to *0.5*, the routing metric combines inconvenience and disturbance equally.

In order to help readers to understand the difference between inconvenience and disturbance, Figure 4-3 is provided as Figure 4-3 (a) and (b) shows the disturbance and inconvenience level of the selected path respectively. In this example, nodes *3*, *8*, *13*, *18* and *23* have bigger transmission range and interference range than the other nodes as shown in Figure 4-3. In these figures, nodes in the third row (node *3*, *8*, *13*, *18* and *23*) have same transmission range and interference range as shown in (a); the others have transmission range and interference range smaller than the nodes in the third row as can be seen by comparing the transmission range or the interference range of nodes in the third row in Figure 4-3 (a) with the transmission range or the interference range of other nodes in Figure 4-3 (b). As aforementioned, disturbance is measured from the outward interference of the node of interest (transmitter's perspective). The disturbance level is defined as the number of nodes within the interference range of the node of interest. Therefore, the total disturbance level of the selected path is the sum of the disturbance of each transmitting node along the path. In Figure 4-3 (a), node *3* and *23* have *7* nodes within its interference range; node *8*, *13* and *18* have *10* nodes within their interference range. Thus, the total disturbance level of this path is *33* as *6* DNs from node *3*, *9* DNs from node *8*, *13* and *18*. On the other hand, the inconvenience is measured from the inward interference of the node of interest, and the inconvenience level is defined as the number of nodes that will cause interference to the node of interest (receiver's perspective). The inconvenience level is defined as the number of nodes that may interfere with the selected path and is the sum of the inconvenience level of each receiving node along the path. In Figure 4-3 (b), it illustrates that nodes in first row and last row do not cause interference to nodes in the third row due to their smaller interference range. Node *3* has an inconvenience level of *2* as there are *3* nodes (node *2*, *4* and *8*) will cause interference on node *3*, but one of them will be the transmitter; node *8* has inconvenience level of *3* (node *3*, *7*, *9* and *13* will cause interference on node *8*); node *13* has an inconvenience level of *3* (only node *8*, *12*, *14* and *18* will cause interference on node *13*); node *23* has an inconvenience level of *2* (only node *18*, *22* and *24* will cause interference to node *23*). Therefore the total inconvenience level of the selected path is *11* as the inconvenience level of *3* on node *8*, the inconvenience level of *3* on node *13*, the inconvenience level of *3* on node *18*, the inconvenience level of *2* on node *23*.



(a)



(b)

Figure 4-3 Disturbance and inconvenience; (a) shows the disturbance level for the selected path; (b) shows the inconvenience level for the selected path

4.3.2 DIR^k Scheme

By changing the power value *k*, DIR^k can help ensure that traffic avoids the congested area by using less frequently used nodes on the edge. In general, the two metrics not only consider reducing the number of DN over the whole path, but also take individual nodes into account.

In Chapter 2.4, we identified how to find a path with the lowest cost by using Dijkstra's algorithm when the link weight is determined.

Based on DIR, the disturbance routing to the power of k (DIR^k) scheme changes the link cost, i.e. the number of disturbed nodes according to its power of *k* (*k* = *2*, *3*, *4*….etc). The definition of the link cost of DIR^k is

$$w_{ij} = \alpha I_j^k + (1-\alpha) D_j^k, \forall i, j \in V, 0 \le \alpha \le 1, k \in N \ge 2 \tag{4.2}$$

This places more emphasis on reducing the disturbance on a per node basis in the system, due to the characteristic of DIR^k which is that the link cost increases exponentially as the degree of *k* gets larger. Therefore, it is preferred to relay traffic through nodes that have fewer DNs around them. In other words, DIR^k selects nodes with a lower impact to their neighbours.

The *k* value is tested from *1* to *6* and DIR^4 ($k = 4$) outperforms other *k* values in terms of DN per hop performance. This is because $k = 4$ places more emphasis on the individual performance than $k = 2$ and *3* due to the network conditions. In other words, each node of DIR^4 increases its weight value enough so that the path can be affected to pick nodes with smaller DN value, despite a higher number of hops, and DIR^4 shows a better performance on selecting nodes around edges of the network, compared with DIR, DIR^2 and DIR^3. The number of DN to the power of *2* and *3* are not enough to divert routes to the network edges. It is found that increasing *k* beyond *4* does not result in any further improvement on selecting nodes with fewer DNs due to the network size and the transmission range of nodes. In general, therefore, it seems that DIR^4 has a better capability of increasing the sensitivity of the metrics to conditions in the network.

4.3.3 DIR_{th} Scheme

Disturbance/Inconvenience based routing with a threshold value (DIR_{th}), increases link weight by value of δ for those nodes with an interference level greater than the threshold value (T). So the definition of the link weight of DIR_{th} is shown below:

$$w_{ij} = \begin{cases} \alpha I_j + (1-\alpha)D_j, & \alpha I_j + (1-\alpha)D_j \leq T \\ \delta + \alpha I_j + (1-\alpha)D_j, & \alpha I_j + (1-\alpha)D_j > T \end{cases}, \forall i, j \in V, 0 \leq \alpha \leq 1 \qquad \textbf{(4.3)}$$

Where $\delta >> \alpha I_j + (1-\alpha)D_j$

The DIR_{th} scheme separates nodes into two groups: Group 1 (G1) contains nodes with the interference level equal to or less than the threshold value; the other one (G2) contains nodes with the interference level that is larger than the threshold value. The important aspect of this scheme is that the link weight is adjusted by determining the threshold value. If the threshold value is too big, and there are many more nodes in G1 than in G2, then G1 dominates, and the scheme performs similarly to DIR; if the threshold value is very small, nodes in G2 dominates and the scheme works similar to the DIR scheme, although the link weight changes to $\delta + \alpha I_j + (1-\alpha)D_j$, and nodes in G2 are still prioritised due to their original interference level.

We can determine a reasonable threshold value for DIR_{th} if the network parameters are given, such as the total number of nodes, network area size, node transmission range etc. Here we illustrate how the threshold value is determined in this chapter.

In [64], it shows that if n nodes are randomly uniformly positioned in an interval $[0, x_m]$, then the probability of n_0 nodes of these n nodes being in the interval $[x_1, x_2]$ (where $0 \le x_1 \le x_2 \le x_m$) is:

$$P(d^* = n_0) = \binom{n}{n_0} p^{n_0} (1-p)^{n-n_0} \tag{4.4}$$

Where the random variable d^* denotes the number of nodes within the given interval $[x_1, x_2]$ and p represents the probability that a node is placed within this interval, $p = \frac{x_2 - x_1}{x_m}$

For $n >> 1$ and $x_2 - x_1 << x_m$, then the probability solution can be approximated with a Poisson distribution i.e.,

$$P(d^* = n_0) = \frac{(np)^{n_0}}{n_0!} \cdot e^{-np} \tag{4.5}$$

for n_0 in the order of $\frac{x_2 - x_1}{x_m} \cdot n$. Let us assume large n and large x_m but keep the ratio of $\rho = n/x_m$ constant. Therefore, the density ρ is the expected number of nodes per unit length. For a given density (ρ), the probability of n_0 nodes within the interval length $x_0 = x_2 - x_1$ is:

$$p(d^* = n_0) = \frac{(\rho x_0)^{n0}}{n_0!} \cdot e^{-\rho x_0} \tag{4.6}$$

The aforementioned process is one-dimensional problem. For the two-dimensional case, the system interval ($[0, x_m]$) can be replaced by the system area A and the subarea A_0 can replace the subinterval x_0. The expected number of nodes per unit area ρ becomes n/A. Therefore, the probability of finding n_0 nodes in an area A can be deduced as:

$$p(d^* = n_0) = \frac{(A_0 n / A)^{n0}}{n_0!} \cdot e^{-\frac{A_0}{A}n} = \frac{(\rho A_0)^{n_0}}{n_0!} \cdot e^{-\rho A_0} \tag{4.7}$$

For a radio range r_0, the coverage area A_0 is πr_0^2. Thus the probability that a randomly chosen node has n_0 neighbours is [64]:

$$p_1 = \frac{(\rho \pi r_0^2)^{n_0}}{n_0!} \cdot e^{-\rho \pi r_0^2} \tag{4.8}$$

From the aforementioned equations, the expected number of nodes within a subarea (πr_0^2) can be determined if the node density ρ is known. The threshold value of DIR_{th} is defined by the number of nodes (n_0) in the interference area ($A_0 = \pi I_0^2$) that provides the maximum probability among all choices for Equation (4.8).

In the DIR_{th} routing metric, if the node's interference is less than the threshold value T, the link weight remains unchanged. On the other hand, if the interference is greater than T, the link weight is set to δ plus the original interference value. The reason for setting the link weight to δ plus the original interference is to distinguish the priority for picking relay nodes that have the interference bigger than T if they are the only nodes that can reach to the destination. By adjusting T in DIR_{th}, it avoids picking those nodes that have higher interference than the threshold value, except those nodes that are the only options to reach the destination node. This routing metric has the advantage of controlling traffic through certain nodes by adjusting its threshold value.

4.3.4 Analysis of Isotonicity and Monotonicity

Here, we will use mathematical equations to show the DIR routing family is isotonic and monotonic. Recall the conditions for isotonicity and monotonicity in Chapter 2.

If there are *m* links in the path *a* and *n* links in the path *b*. As the DIR routing metric is defined in equation (4.1), therefore the weight of path *a* is

$$w_A = \alpha \sum_{A=1}^{m} I_A + (1-\alpha)\sum_{A=1}^{m} D_A \tag{4.9}$$

The weight of path *b* is:

$$w_B = \alpha \sum_{B=1}^{n} I_B + (1-\alpha)\sum_{B=1}^{n} D_B \tag{4.10}$$

Therefore, the total path weight of path *a* concatenated with path *b* is

$$\begin{aligned} W(a \oplus b) &= W_A + W_B \\ &= \alpha \sum_{A=1}^{m} I_A + (1-\alpha)\sum_{A=1}^{m} D_A + \alpha \sum_{B=1}^{n} I_B + (1-\alpha)\sum_{B=1}^{n} D_B \\ &= \alpha\left(\sum_{A=1}^{m} I_A + \sum_{B=1}^{n} I_B\right) + (1-\alpha)\left(\sum_{A=1}^{m} D_A + \sum_{B=1}^{n} D_B\right) \\ &= W(b \oplus a) \end{aligned} \tag{4.11}$$

Since *I* and *D* are the inconvenience and disturbance levels respectively whose levels are related only to the number of nodes disturbed or within the interference range of object node. Thus, *I* and *D* are positive integers; as the priority factor α is between 0 and 1. Therefore, the following conditions are true.

$$\alpha\sum_{B=1}^{n} I_B \geq 0$$
$$\alpha\sum_{A=1}^{m} I_A + \alpha\sum_{B=1}^{n} I_B \geq \alpha\sum_{A=1}^{m} I_A$$
$$\alpha(\sum_{A=1}^{m} I_A + \sum_{B=1}^{n} I_B) \geq \alpha\sum_{A=1}^{m} I_A \quad \textbf{(4.12)}$$

$$(1-\alpha)\sum_{B=1}^{n} D_B \geq 0$$
$$(1-\alpha)\sum_{A=1}^{m} D_A + (1-\alpha)\sum_{B=1}^{n} D_B \geq (1-\alpha)\sum_{A=1}^{m} D_A$$
$$(1-\alpha)(\sum_{A=1}^{m} D_A + \sum_{B=1}^{n} D_B) \geq (1-\alpha)\sum_{A=1}^{m} D_A \quad \textbf{(4.13)}$$

As can be seen from equation (4.11), the total path weights of path *a* connected priori or posterior with path *b* are the same. Therefore the DIR routing metric is monotonic as it obeys the following conditions which the weight of a path does not decrease when prefixed or appended by another path:

$$W(a) \leq W(a \oplus b) \quad \textbf{(4.14)}$$

$$W(a) \leq W(c \oplus a) \quad \textbf{(4.15)}$$

Here, let us analyse the isotonicity of the DIR routing metric by given three paths *a*, *b* and *c* with *m*, *n* and *x* links respectively. Therefore, the weight of path *a* and *b* are as same as shown in the equation (4.9) and (4.10) respectively. The weight of path *c* is:

$$w_C = \alpha\sum_{C=1}^{x} I_C + (1-\alpha)\sum_{C=1}^{x} D_C \quad \textbf{(4.16)}$$

Thus, the total path weight of path *a* concatenated with path *c* is

$$
\begin{aligned}
W(a \oplus c) &= W_A + W_C \\
&= \alpha \sum_{A=1}^{m} I_A + (1-\alpha)\sum_{A=1}^{m} D_A + \alpha \sum_{C=1}^{x} I_C + (1-\alpha)\sum_{C=1}^{n} D_C \\
&= \alpha(\sum_{A=1}^{m} I_A + \sum_{C=1}^{x} I_C) + (1-\alpha)(\sum_{A=1}^{m} D_A + \sum_{C=1}^{x} D_C) \\
&= W(c \oplus a)
\end{aligned}
\tag{4.17}
$$

Also, the total path weight of path *b* connected with path *c* is

$$
\begin{aligned}
W(b \oplus c) &= W_B + W_C \\
&= \alpha \sum_{B=1}^{n} I_B + (1-\alpha)\sum_{B=1}^{n} D_B + \alpha \sum_{C=1}^{x} I_C + (1-\alpha)\sum_{C=1}^{n} D_C \\
&= \alpha(\sum_{B=1}^{n} I_B + \sum_{C=1}^{x} I_C) + (1-\alpha)(\sum_{B=1}^{n} I_B + \sum_{C=1}^{x} D_C) \\
&= W(c \oplus b)
\end{aligned}
\tag{4.18}
$$

If, *W(a)* ≤ *W(b)*. Since *I* and *D* are positive integers, and the priority factor α is between 0 and 1. Then the following conditions are true.

$$
\begin{aligned}
& W(a) \le W(b), \\
& \alpha \sum_{A=1}^{m} I_A + (1-\alpha)\sum_{A=1}^{m} D_A \le \alpha \sum_{B=1}^{n} I_B + (1-\alpha)\sum_{B=1}^{n} D_B, \\
& \alpha \sum_{A=1}^{m} I_A + (1-\alpha)\sum_{A=1}^{m} D_A + \alpha \sum_{C=1}^{x} I_C + (1-\alpha)\sum_{C=1}^{n} D_C \le \\
& \alpha \sum_{B=1}^{n} I_B + (1-\alpha)\sum_{B=1}^{n} D_B + \alpha \sum_{C=1}^{x} I_C + (1-\alpha)\sum_{C=1}^{n} D_C, \\
& \alpha(\sum_{A=1}^{m} I_A + \sum_{C=1}^{x} I_C) + (1-\alpha)(\sum_{A=1}^{m} D_A + \sum_{C=1}^{x} D_C) \le \\
& \alpha(\sum_{B=1}^{n} I_B + \sum_{C=1}^{x} I_C) + (1-\alpha)(\sum_{B=1}^{n} I_B + \sum_{C=1}^{x} D_C)
\end{aligned}
\tag{4.19}
$$

Therefore the DIR routing metric is isotonic as it obeys the following conditions.

$$
W(a) \le W(b) \to W(a \oplus c) \le W(b \oplus c) \tag{4.20}
$$

$$W(a) \leq W(b) \rightarrow W(c' \oplus a) \leq W(c' \oplus b) \tag{4.21}$$

4.3.5 Network Environment

Let us now verify those routing metrics in a Fixed Transmission Range Scenario (FTRS). In this network environment, there are *100* stationary wireless nodes located randomly in an area of 40×40 km^2. The traffic model is quite simple in this chapter as we assume an infinite packet length for each source node which means once a connection has been established; it will remain in the network permanently. Data are collected in different numbers of source-to-destination pairs in which every source node transmits to the same destination node. More practical traffic models are introduced in chapter 6 and 7 such as call basis and file length basis. The transmission radius (TR) of each node is set to an identical level, which is between *2* to *10* km and the interference radius (IR) is twice the TR for each node. The sink/destination node is picked randomly in the network. The parameters used in the network are listed in Table 4-1.

The connectivity is defined in terms of the number of clusters. For a *100* node network, 1 cluster means it is fully connected and *100* clusters indicate no node is connected to any of others. The level of connectivity in terms of the number of clusters against the different fixed transmission range for the nodes is calculated based on Equation (4.8) and it is shown in Figure 4-4. The network is not fully connected if the transmission range of all nodes is set to less than *5* km for this scenario. It shows that when TR is equal to or greater than 6 km, the network is usually fully connected which means that each node can be reached by any other node either directly or through other nodes. The bigger the TR, the more nodes that are disturbed. So there is a trade-off for choosing the transmission range.

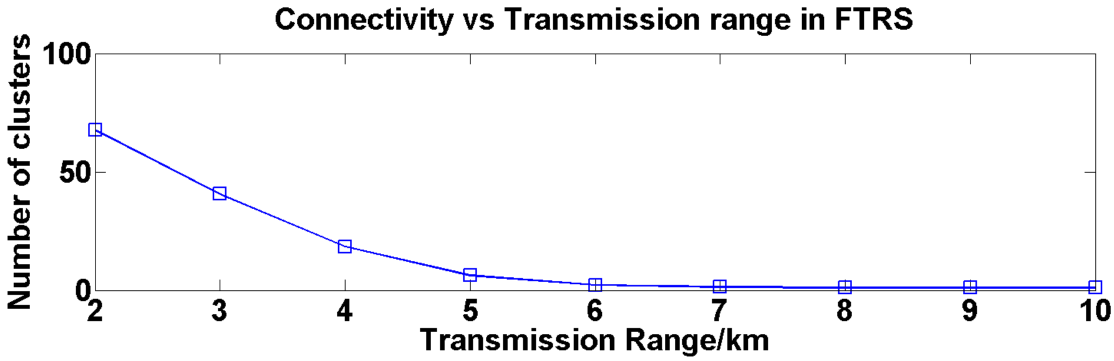


Figure 4-4 Network connectivity against transmission range

Parameters	**Values**
Number of Nodes	*100* wireless nodes
Network Model Size	*40* km × *40* km
Network Topology	Random Located
Transmission Radius	*2* km to *10* km
Interference Radius	*2* × Transmission Range
Channel number	*1*
Sink node	Random select
Monte Carlo Simulation	*2000* iterations

Table 4-1 Key parameters of the network

4.4 Performance

In this section, we testify to the effectiveness of different routing mechanisms proposed in the aforementioned sections. Example scenarios are given to show the key concepts of DIR routing metrics, and they are compared with the shortest path by hops with the same topology. A Monte-Carlo simulation is used to examine the comparative performance of the DIR routing and shortest path metrics (by distance/by hops). In this section, the interference priority factor is set to *0.5*.

4.4.1 Congestion Level and Virtual Capacity

Results are compared through not only the number of disturbed nodes, but also with congestion level, which can illustrate more practical interference levels due to traffic flows. The congestion level of node j is defined as [53]:

$$CL_j = \sum_{k\_j=0}^{NI_j} R_{k\_j}, \forall j \in V \tag{4.22}$$

Where NI_j is the number of interfering nodes to node j, R_{k_j} is the number of routes going through node k_j, which is one of the interferers, using channel k, and R_0 in particular indicates the number of routes going through the node of interest itself. In this chapter, we use a co-channel model to start with as it is the worst case scenario for considering the capacity of ad hoc networks. Therefore, the congestion level of a node is the summation of the number of activated links within its interference range. In Figure 4-5, the congestion level of N_0 is *8* as there are *8* concurrent links within the interference range of node N_0.

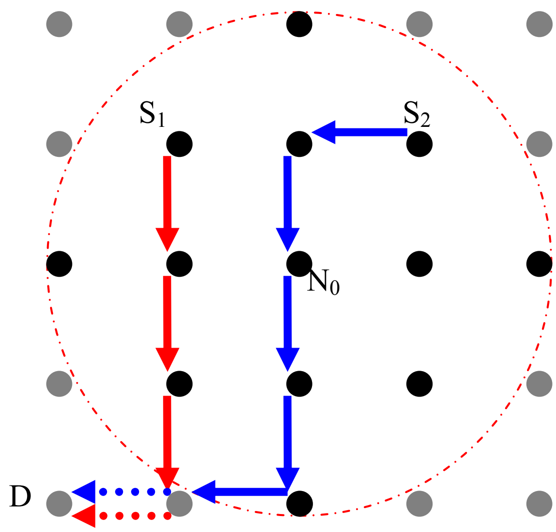


Figure 4-5 Example of congestion level

Link capacity is influenced by a number of factors, such as power level of the transmitter, distance between the nodes, the spectrum that is available for the transmission, noise, intra-flow and inter-flow interference. As a co-channel scheme is considered for this chapter, the virtual capacity is only determined by intra-flow and inter-flow interference and node bandwidth and is defined as:

$$C_j = \frac{B_j}{CL_j + 1}, \forall j \in V \tag{7}$$

Where B_j is the bandwidth that can be utilised by node j, and CL_j is the congestion level of node j.

4.4.2 Snapshot Results

In this scenario, each node has an identical power delivering a successful transmission range of *7* km. The reason for choosing *7* km as the transmission range is because it usually builds a fully connected network given the node density deployed over the size of area selected as shown in Figure 4-4.

We will use the contour graphs (Figure 4-6, Figure 4-7 and Figure 4-8) to show the congestion level which is related to the virtual capacity of each node reciprocally (if bandwidth is normalized) when using different routing metrics. There are *2* source nodes and *2* sink nodes, which are selected from corners of the network and they are located in each corner separately. Each routing metric will be evaluated by using the same source and destination nodes pair. We assume nodes are active all the time and able to sense the environment to establish the interference level. Figure 4-6 shows the congestion level of each node when they choose the shortest path by hops routing (SH). We can see that the routes are selected with the lowest number of hops through the middle of the network as expected. For example, nodes around *28* and *39* have higher congestion level than others due to the traffic relaying through the heavy congested area. The congestion level around node *60* is also high although traffic is not flowing through it; its neighbours use the shared bandwidth for relaying.

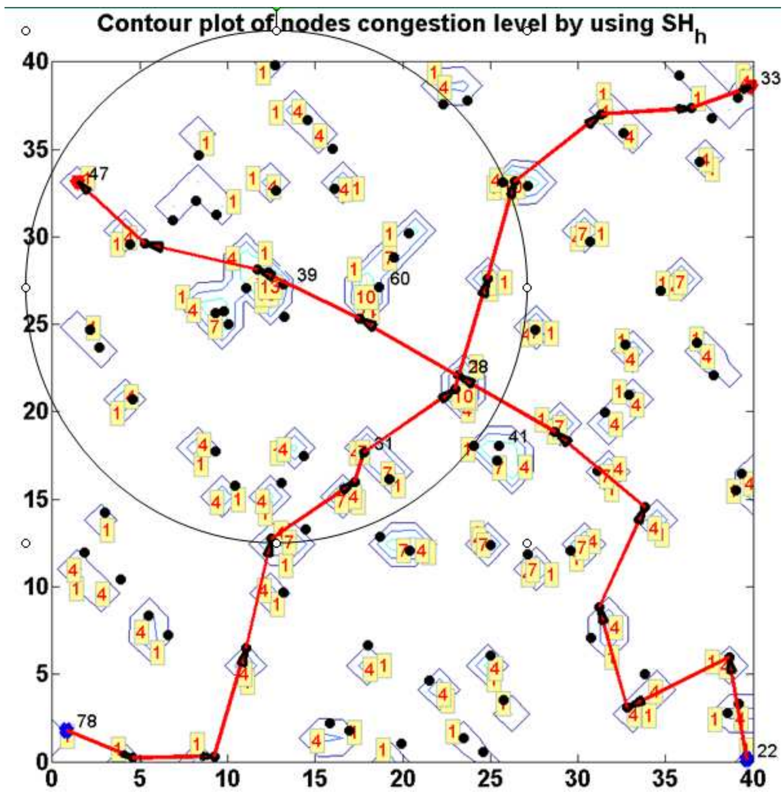


Figure 4-6 Contour plot of node congestion level by using SH

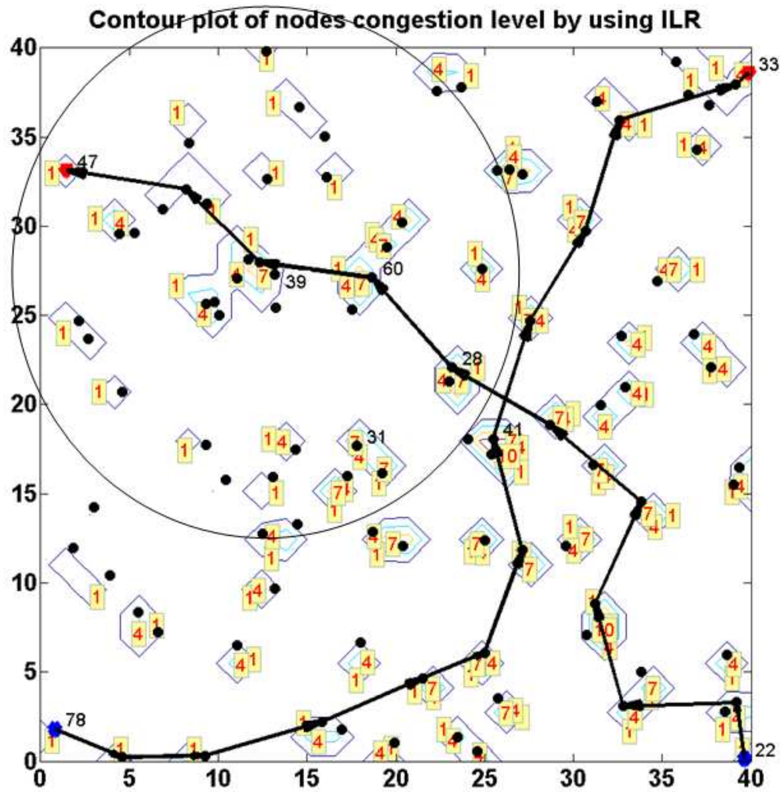


Figure 4-7 Contour plot of node congestion level by using DIR

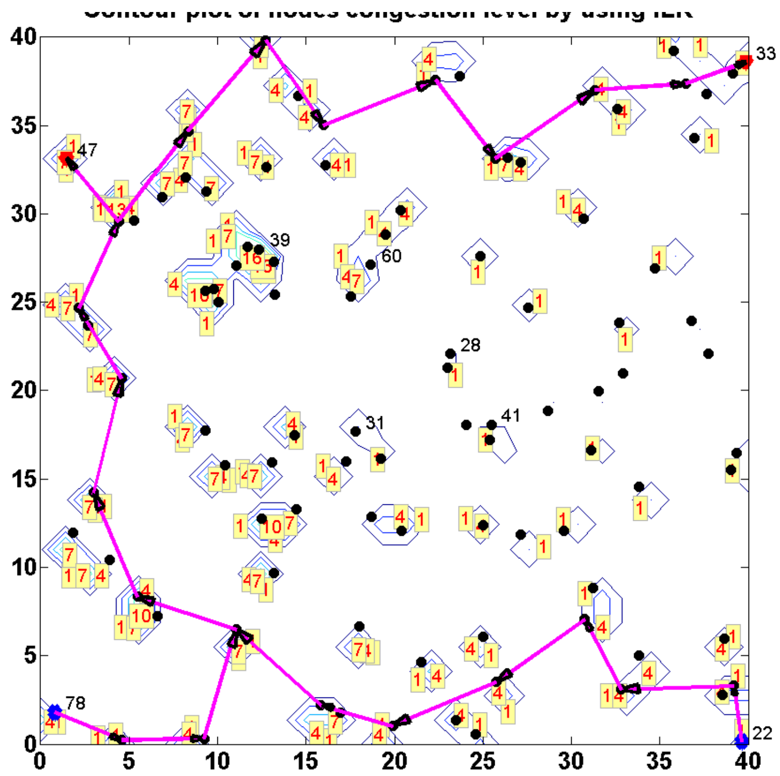


Figure 4-8 Contour plot of node congestion level by using DIR^2

As can be seen from Figure 4-7, the congestion level of the nodes is decreased by using DIR as the routing metric routes traffic more through the edge of the network, compared with the SH. The black circle in Figure 4-6 and Figure 4-7 indicates the interference range of node *39*. By using DIR, the congestion level of node *39* is reduced to *7* (compared to *13* by using SH) as there are *6* links from path *78→33* dropped outside the interference range of node *39*. Also the bottleneck of the nodes congestion level has been improved (from *13* to *7* and *10* to *7* for node *39* and *60* respectively). Node *31* is a relay node when the SH is used. However, node *31* does not relay the traffic when DIR is applied due to the ability of DIR to avoid heavily interfered nodes along the path. In Figure 4-8, DIR^2 (where k = *2*) shifts the traffic to the edge of the system (here we define the 'edge' as locations that are subject to less traffic). As DIR^k sets the weight of the interference level according to an exponential increase (higher k value), it performs not only like the DIR scheme, which takes the interference level along the path into account, but also more radically than DIR, in that it selects the relaying nodes with fewer interfering nodes around them. Thus, routes are located around the edge of the network to avoid the congested area. DIR_{th} has identical path tracks for this scenario with same source to destination pairs.

4.4.3 Monte Carlo Results

A uniform geographic distribution of traffic is assumed again to be generated by the nodes simultaneously in the system. This is a worst case scenario, where the system is running at its maximum overall capacity and the most severe interference level is experienced due to the single channel environment. The disturbance/inconvenience based routing metrics will be examined, and then the schemes will be compared with MIR and conventional shortest path by hops routing (SH). Figure 4-9 shows results with a high traffic load for which all nodes in the network are considered to be the source node.

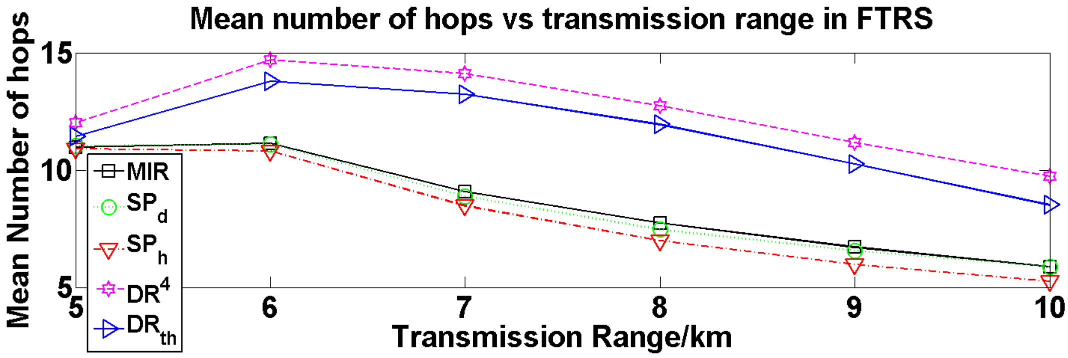
Figure 4-9 presents the routing metrics' performance in terms of mean number of hops, mean number of DNs and mean number of DNs per hop for different fixed transmission ranges of the nodes respectively. The routing metrics' performance is almost identical when the transmission range is set to less than *5* km, which is an unconnected network as the routing metrics have fewer options for selecting nodes to distribute the traffic. So we only compare the differences for each of the routing metrics between the transmission range of *5* km and *10* km in Figure 4-9. Figure 4-9 (a) shows DIR^4 and DIR_{th} take more hops than the other routing metrics as expected. The DIR^k scheme due to the power degree k ($k \geq 2$), significantly prefers to use fewer interfered nodes to relay, and so is likely to choose an indirect path which is longer in a random topology. For example, if we consider two alternative routes: one has one relaying node with *4* disturbed nodes; the other has two relaying nodes with *3* disturbed nodes each. DIR^4 will choose the longer route ($3^4+3^4 < 4^4$), while MIR will choose the shorter route ($3+3 > 4$). The higher the value of k for DIR^k, the more hops that will be taken to relay the packets. DIR_{th} is forced to relay the traffic through the nodes which have fewer disturbed nodes than its determined threshold value. Moreover, it shows that the SP_h uses the least mean number of hops to transmit the packet as we expect. Figure 4-9 (b) indicates DIR^4 and DIR_{th} have a higher cost in terms of disturbed nodes compared with MIR and SP. This is because the DIR^k and DIR_{th} schemes distribute traffic towards the edge of network, thus more hops will be used. Consequently, it has the impact of raising the total number of disturbed nodes along the path from the source to the destination node. MIR causes the least mean number of disturbed nodes in Figure 4-9 (b) as expected because it aims to do so. In (c), DIR^k and DIR_{th} outperform MIR, SP_d and SP_h in terms of minimising the number of disturbed nodes per hop. This indicates that DIR^k and DIR_{th} routing take the individual node's interest over the end-to-end performance.

Figure 4-9 (b) also shows that the larger the transmission range, the more nodes that are disturbed. So there is a trade-off for choosing the transmission range. According to the result in (a), all routing metrics have a peak value for the hop number at the transmission range of *6* km. Moreover, this also establishes a fully connected network with a probability of 99% in Figure 4-4. This proves that the best performance of the network, which is used in this chapter, is achieved when nodes set the transmission range to *6* km in the Fixed Transmission Range Scenario (FTRS).

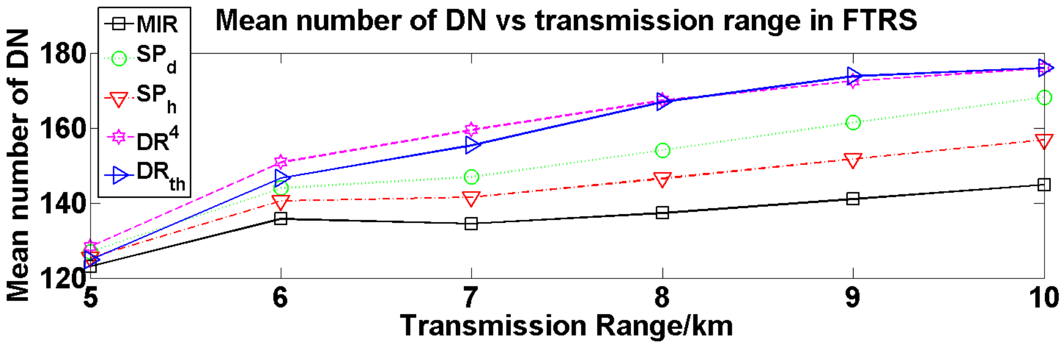
Although MIR outperforms the other routing metrics in terms of mean number of DN, the mean number of DN per hop can illustrate how well routing metrics can cope with individual node/link performance rather than end-to-end performance. For example, in cognitive radio networks, this type of routing metric can be applied amongst secondary users as they are encouraged to relay traffic through the edge of network so that primary users will not be interfered with by their transmissions. This can be done by modifying the metric from taking the number of DNs to the number of primary users. Therefore, from a per hop perspective, this implies that the fewer number of primary users per hop, the smaller the probability that the selecting node interferes with primary users. The routing metric design is considered to be more intelligent if it can account for individual node/link performance. We can compare these routing metrics by calculating the Disturbed Nodes per Hop Reduction (DNHR) at the transmission range of 6 km in Figure 4-9 (c). The DNHR equation is shown below [52]:

$$DNHR = \frac{(Mean\ A_{DNH} - Mean\ B_{DNH})}{Mean\ A_{DN}} \times 100, \qquad \textbf{(4.23)}$$
$$A_{DNH}, B_{DNH} \in [SP_d, SP_h, MIR, DR_{th}, DR^k], A_{DNH} \neq B_{DNH}$$

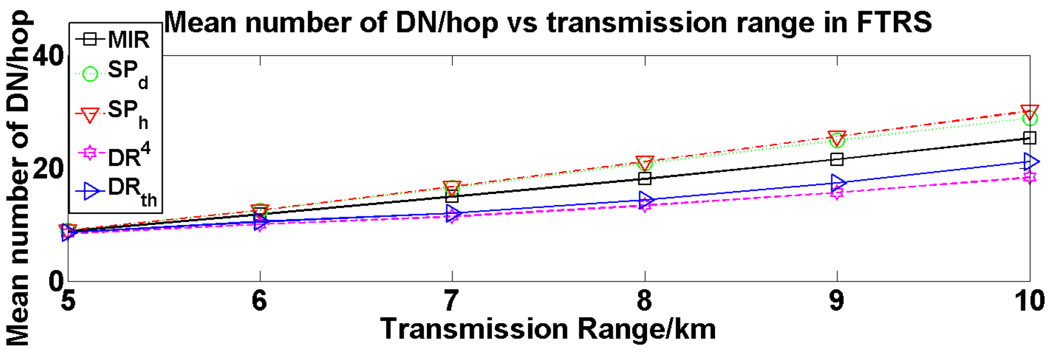
From the data obtained from the results in Figure 4-9 (c), at the transmission range of 6 km, DIR[k] has an average reduction of *20%* on a DN per hop basis compared with the poorest routing metric scheme SP_h, where DIR_{th} also achieves an average reduction of *16.5%*. This indicates DIR[k] is more focused on reducing the disturbance on a per node basis rather than on the whole route basis.



(a) Mean number of hops vs transmission range



(b) Mean number of DN vs transmission range



(c) Mean number of DN/hop vs transmission range

Figure 4-9 Simulation results for FTRS: (a) Mean number of hops; (b) Mean number of DN; (c) Mean number of DN/hop vs TR

DIR^4 performs the best out of all the routing metrics in terms of number of DNs per hop, because DIR^k is designed for picking relaying nodes that have as few disturbed nodes as possible. This indicates DIR^k is more focused on reducing the disturbance on per node basis rather than on the whole route basis. As a result, the higher the value of *k*, the fewer disturbed nodes per hop. DIR_{th} can separate nodes to two different groups by setting the threshold value correctly; and thus it is more robust than the other routing metrics mentioned in this chapter. Moreover by defining the threshold value differently, this scheme could also split nodes into more than *2* groups, providing an additional service differentiation.

Figure 4-10 shows the performance of average congestion level versus traffic load for each of the aforementioned routing metrics. The scenario parameters are almost the same as in Table 4-1, except there are a variable number of source-to-destination pairs. This has been obtained from a Monte-Carlo simulation after *1000* iterations with source-to-destination pairs *2* to *98*. The result shows that DIR^k tends to have lower level of congestion than others, especially when the traffic loads increase. This indicates that DIR^k can reduce the bottleneck of the system by reducing the network congestion level. DIR^2 can mitigate the average congestion level by *15%* compared with shortest path at high traffic load. Therefore the heavier the traffic is in the system, the more advantage DIR^k can deliver to improve the end-to-end congestion level. This is because DIR only reduces the interference on a whole path basis, irrespective of which individual nodes are selected for relaying the traffic. By changing the *k* value of the routing metric, it has the ability to alter routes through the network in response to the interference or congestion.

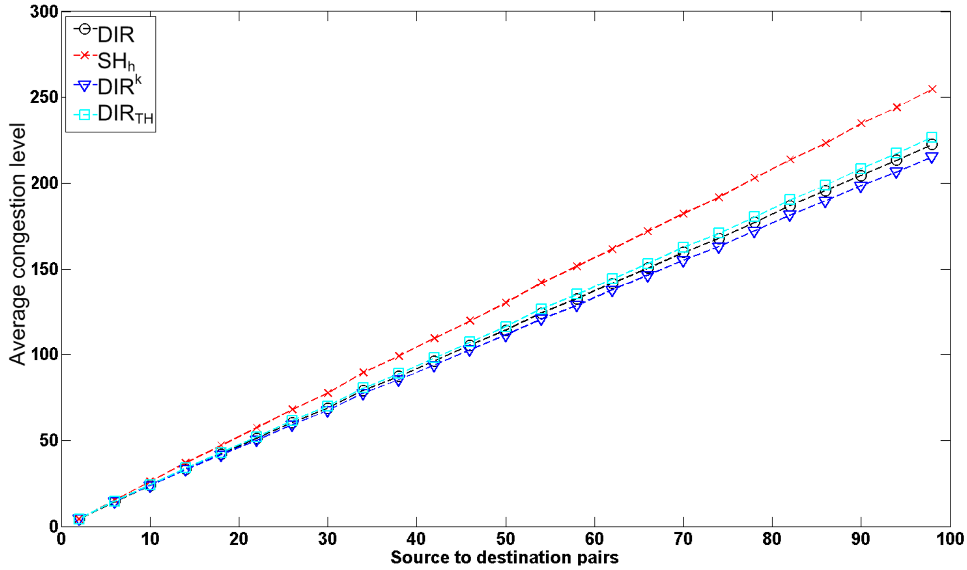


Figure 4-10 Average congestion level against traffic load measured in number of active source destination pairs

4.5 Conclusion

This chapter shows the early work of designing a family of routing metrics to avoid congested areas. Disturbance/Inconvenience based routing metric (DIR) takes both outward and inward interference into routing metric design. The extensions of DIR (DIR^k and DIR_{th}) have the ability to adjust their link weight so that they can take individual node states into account as well as the end-to-end perspective. DIR^k can treat the interference on the same node/link differently by adjusting the link/node weight to the power of *k*. By changing the *k* value, DIR^k is able to decide to select intermediate nodes which provide the lowest interference on an end-to-end basis or individual basis due to the exponential impact on links/nodes weight. DIR_{th} separates links/nodes into two groups due to the interference threshold value.

There are still many limitations of this DIR routing metric design. For example, the routing metric cannot adapt well to environment changes as it only takes disturbed node number into account, regardless of traffic flows, bottleneck nodes and channel assignment etc. In addition, DIR selects routes by going through nodes with fewer DN. This characteristic results in unnecessary hops which lead to extra relaying burdens on the whole network. Therefore, it is recommended to apply DIR in a network scenario where traffic load is relatively low or there is sufficient radio spectrum to fulfil the traffic demand, so that it can route around congested areas without limiting network capacities due to extra relaying hops. More sophisticated routing metric designs will be shown in later chapters.

Chapter 5

5 Routing Metric Design to Improve End-to-end Bottleneck Capacity

Contents

5.1 Introduction

One advantage of a wireless ad hoc network is its multi-hop feature as nodes can forward packets from source to destination on a hop-by-hop basis. However, relaying can reduce network capacity as nodes contend for capacity not only with others serving on routes nearby, but also with those nodes taking part in relaying on the same path. The capacity of an ad hoc network can be surprisingly low due to these inter-flow and intra-flow contentions [30].

In the previous chapter, we presented the early work of routing metric design by taking the number of disturbed nodes into account to avoid congested areas. However, this routing metric design cannot cope well with environmental changes due to traffic flows and varying link/node capacities. For example, a route that is selected to go through a node with low capacity may result in a longer delay or lower throughput even when other nodes along the path may have sufficient capacity. Therefore, it is desirable to find a routing metric design that can not only improve the overall network capacities but also avoid creating bottleneck nodes in wireless ad hoc networks.

The purpose of this chapter is to design a routing metric, which is referred to as bottleneck-aware routing (BAR), that takes the current node capacity into account as well as the bottleneck node location to improve the bottleneck capacity in a heterogeneous ad hoc network. It is inspired by capacity based-routing [53] which incorporates the node capacity into the routing metric design in order to improve the capacity of the wireless ad hoc networks.

The details of the capacity model used are given in section 5.2. Then, section 5.3 reviews capacity-based routing (CBR), which is followed by the proposed bottleneck-aware routing (BAR) metric design in section 5.4. Section 5.5 outlines the network scenario which is used in this chapter. Comparative simulation and analytical results are presented for BAR, CBR and shortest path by hops (SH) in section 5.6. Finally we will draw the conclusions in section 5.7.

5.2 Capacity Model

In this section, the capacity model is defined to include node capacity and node virtual capacity.

5.2.1 Node Capacity

In this chapter, a heterogeneous network with *3* different types of node (basic node, aggregation node and landmark node) is used.

- Basic nodes have lowest capability for transmitting data with low bandwidth ranges from *100* Kbps to *1* Mbps (e.g. sensor nodes in wireless sensor networks)
- Aggregation nodes have medium capability for transmitting data. These nodes are responsible for aggregating traffic from multiple low capability nodes and have medium bandwidth from *1* Mbps to *2* Mbps (e.g. cluster head)
- Landmark nodes have a high capacity for transmitting data with high bandwidth from *2* Mbps to *4* Mbps. Those nodes can operate with advanced techniques (e.g. directional antenna) that will handle trunked traffic for communicating directly with the high-speed infrastructures such as a headquarter in a battlefield

The node capacity (C) is determined by their node types. Network capacity can be improved by better exploiting the network hierarchies of ad hoc networks [53].

5.2.2 Node Virtual Capacity

The virtual capacity of a node (C_V) is introduced here as the capacity allocated to the link for a specific routing. It is a portion of the raw capacity of the node ($C_V \in C$) and it is determined by the co-channel interference (node congestion level which has been defined in the previous chapter). We assume fair scheduling TDMA is used so that each link that competes for the same channel can be assigned a different time slot with an equal length. This scenario implies that the route has to share the bandwidth not only with routes going through the node of interest, but that it also has to share the bandwidth with the routes going through the interferers of the node of interest. Therefore, the virtual capacity of node N_0 is the raw capacity of the channel divided by the congestion level for its routing task. For example, Figure 5-1 shows that the virtual capacity of node N_0 is $C/8$ as there are *8* links going through the interference range of N_0, and the raw capacity is then evenly divided for each transmission as shown in Figure 5-2.

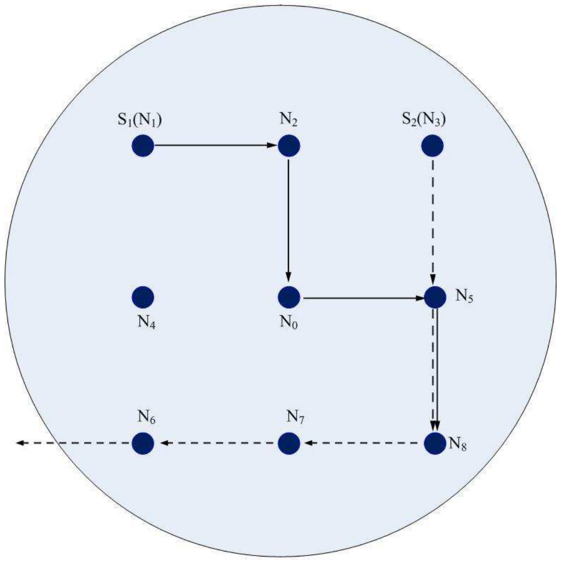


Figure 5-1 Example of traffic through the network

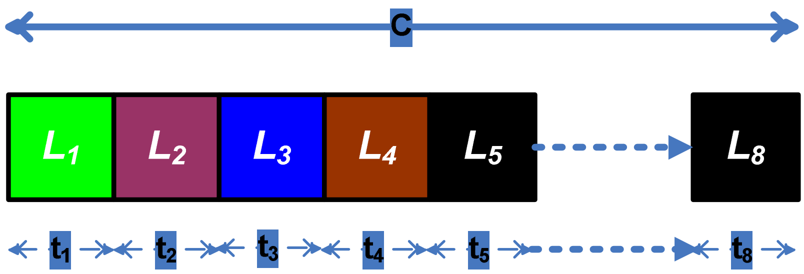


Figure 5-2 Capacity usage at N_0, including usage by interference links.

5.3 Capacity Based Routing

In heterogeneous networks, nodes have different sending rates, transmit powers and antenna gains. These factors result in a different capacity in each direction on a link. Traditional ad hoc routing metrics, like shortest path, cannot take these different link capacities into account. Higher capacity links might remain unused and lower capacity links might end up being crowded. As a result, it is crucial for an ad hoc network to relay more traffic through the higher capacity links to improve load balancing. Figure 5-3 demonstrates an example where the use of a longer route in terms of hop number could be desirable due to the preferable link capacity on the route.

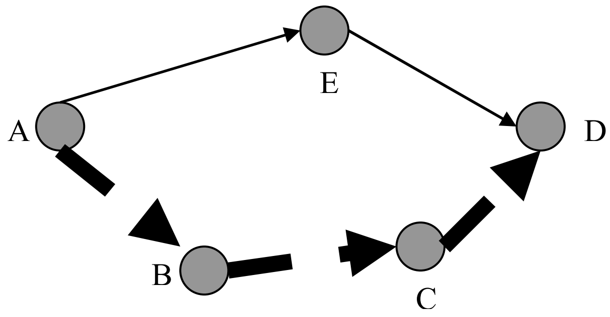


Figure 5-3 Routing from A to D. The dotted route is preferred due to the link capacity is higher on this route.

It is desirable to shift the traffic from a lower capacity node to those which are more capable to relay. Since the capacity in this chapter is mainly determined by active traffic interactions (intra-flow and inter-flow interference), capacity-based routing (CBR) can divert the upcoming traffic to an uncongested area in order to make the whole network more scalable. Here we recall the CBR metric which is shown in Chapter 2, as the link weight of CBR is defined by [53]:

$$w_{ij} = \frac{1}{C_{v\_j}}, \forall i, j \in V \tag{5.1}$$

Where w_{ij} indicates the weight value of the link (from node i to node j), and C_{v_j} indicates the virtual capacity of node j. The virtual capacity of node j is determined by the maximum capacity of the node (check Table 5-1 for each node type) divided by the congestion level this node suffers:

$$C_{v\_j} = \frac{B_j\,(Mbps)}{CL_j} \tag{5.2}$$

By using Dijkstra's algorithm, CBR prefers to select nodes with higher capacities, with routes established based on the maximisation of the accumulated impact capacity on an end-to-end basis.

End-to-end bottleneck capacity, introduced in Chapter 3, is constrained by the minimum capacity value along the path. If the node upstream of the bottleneck node injects more packets into the link than the bottleneck node can forward. Thus delay will increase as packets get stuck at the bottleneck and throughput reduces as these packets are eventually dropped by the congested node. Therefore, it is important for routing metric design to be aware of the bottlenecks and if possible, relay traffic by avoiding the bottleneck nodes as well as nodes nearby them due to the possibility of co-channel interference.

5.4 Bottleneck-aware Routing

Since the bottlenecks are a limitation to the end-to-end performance, routing metrics should take the impact of the bottleneck node into account when selecting routes. There are other routing metrics that have been carried out to improve capacity, load balancing, and hotspot problems such as capacity-based routing (CBR) [53], DLAR [65] and HMP [66]. Liu's capacity-based routing [53] aims to improve network capacity by selecting links with higher capacity on an end-to-end basis without accounting for the impact on the network caused by individual bottleneck links. Lee and Gerla demonstrated a dynamic load-aware routing algorithm (DLAR) [65] which considers the traffic load of the intermediate nodes as the main route selection criterion. DLAR focuses on selecting routes that have the least number of intermediate nodes that have packets buffered by more than a threshold value. This scheme neglects inter-flow interference as in practice the traffic that relays through the nearby nodes can also increase the severity of the bottlenecks. Lee and Campbell presented a hotspot mitigation protocol (HMP) [66] where hotspots represent transient but highly congested regions in wireless ad hoc networks. This solution focuses on alleviating the congested area but fails to take the individual bottlenecks into account. To the best of our knowledge, there are no comprehensive studies and good solutions for routing metrics for scenarios where there is a wide variety of node types and capabilities (e.g. low, medium and high capacity nodes), that also optimise end-to-end performance, by taking into account local area based congestion.

5.4.1 Routing Metric Design

In this section, the routing metric design of BAR is provided. Bottleneck-aware routing (BAR) selects nodes that have a maximum capacity value on a multi-hop transmission path in a similar manner to CBR, but also routes around any bottlenecks. Here the link weight of BAR is defined as:

$$w_{ij} = \begin{cases} \frac{1}{C_j}, j \notin BN \\ \frac{1}{C_j} + \delta, j \in BN \end{cases}, \forall i, j \in V \quad \textbf{(5.3)}$$

Where BN is a set that contains the end-to-end bottleneck nodes of each traffic flow and nodes within the interference range of those end-to-end bottleneck nodes, and δ is a punishment value. If the node is not one of the bottlenecks or the interferer of a bottleneck, the weight remains the same as with CBR. If however the node is either one of the bottlenecks or their interferers, the weight is increased as a punishment by a value δ. The assumption is made here that the interferer node can be informed by the bottleneck node. The discussion of how this is done is beyond the scope of this thesis. The routing protocol associated with the bottleneck-aware routing metric design will be given in the following section to help each node be aware of the other's capacity as well as the locations of end-to-end bottleneck nodes. The bottleneck-aware routing metric is monotonic as weight values are all positive and it is isotonic due to the fact that the subsequent path choice does not affect the weight value of the predecessor path since the current path is calculated and selected based on the weight value of each link from the previous event.

For the scenario here a punishment value of *7* is chosen as this is the average number of nodes within *1* hop distance. The calculation is based on equation (4.6) in Chapter 4 and the network parameters can also be found later within this chapter. There is a trade-off between the punishment values. If the value is too small, routes cannot be fully alerted to avoid going through the congested areas, but if it is too large, it could cause significant relaying, potentially deteriorating future traffic demands.

5.5 Network and Traffic Model

The proposed routing metric will be examined in a *10*-by-*10* grid network environment. There are three different types of nodes in this network: landmark nodes, aggregation nodes and basic nodes. The key parameters are shown in Table 5-1. This is a fully connected scenario. Nodes that have the least number of potential connecting links are located in the corners, where they have just *2* neighbours, with nodes in the middle having the most connections with *4* neighbours. We assume routes do not change during their life-time once they are established. This is convenient for nodes to sense the states of the network and to reduce the route oscillation problem [67].

Key parameters	**Value**
Network size	40×40 m^2
Number of nodes	*100*
Number of landmark nodes	*20*
Number of aggregation nodes	*20*
Number of basic nodes	*60*
Node's transmission range	*6* m
Node's interference range	*12* m
Capacity of landmark link	*4* Mbps
Capacity of aggregation link	*2* Mbps
Capacity of basic link	*1* Mbps
Mean duration of each connection per source node	*0.2* seconds
Inter-arrival distribution range per source node	*0.25* to *6* arrivals/seconds

Table 5-1 Parameter values used in the example scenario

This is a call based ON-OFF traffic model. The mean arrival and the mean duration of each route connection follow a Poisson distribution. All traffic originates at the left edges of the grid network and is forwarded to the right edge. The middle nodes do not originate any traffic. The sources and destinations are selected on each edge of the network as we want to analyse the multi-hop relaying characteristic of each routing metric across the network. Aggregation nodes are selected randomly in the middle. The traffic model in this chapter is more realistic than the traffic model used in the previous chapter. In the previous chapter, once a route connection is established, it remains in the network until the simulation finishes. In this chapter, the arrival and duration of traffic flows have negative exponential distribution. A flow will arrive at each source *10* times during the simulation time. The routing metrics are examined on an event basis. An event occurs when an end-to-end traffic flow is established (ON) or deactivated (OFF) in the network. The maximum number of concurrent routes that can be in operation at a single time is 10.

5.6 Performance

In this section, we examine the effectiveness of different routing mechanisms among shortest-path by hops (SH), capacity based routing (CBR) and bottleneck-aware routing (BAR). Firstly, an example of a snapshot scenario is given to show the improvement in end-to-end bottleneck capacity by using BAR, compared with SH in Figure 5-4 and Figure 5-5. Figure 5-6 shows the CDF of end-to-end bottleneck capacity with different routing metrics at an average traffic load of *3* traffic flows. The comparative performance of end-to-end bottleneck capacity against traffic load will be shown in Figure 5-7.

Figure 5-4 and Figure 5-5 show each node's average congested levels for SH and BAR routing metrics respectively.

- A circle indicates node congestion level, the bigger the circle, the more congestion this node is suffered
- Dark lines illustrate the concurrent traffic flows in the network
- Dots in the middle are the end-to-end bottleneck nodes due to their node capacity and traffic locations

- A cross indicates an aggregation node

In Figure 5-4, SH illustrates that nodes in the middle become very congested as expected, due to the traffic patterns that are generated across the network from left to right, given that SH only selects paths with minimum hop count. This is the worst case for load balancing which leads nodes in the middle of the network to become bottlenecks, with capacity being wasted around the edge.

On the other hand, BAR finds the path by exploiting the highest capacity nodes to relay the traffic, and more importantly, BAR routes around bottleneck links. This improves the load balancing as can be seen in Figure 5-5, where the general number and levels of bottlenecks are reduced by the BAR routing metrics in comparison with SH. The capacity is designed to take intra-flow and inter-flow interference into account. BAR maximises the possibility to improve the network throughput by allowing concurrent transmissions. Flows are shifted from the middle to the edges of the network.

The graph of CBR, which shows the average congestion level of each node during the simulation time, looks similar to Figure 5-5 as BAR is designed based on CBR. Therefore, we will not show the congestion level graph of CBR.

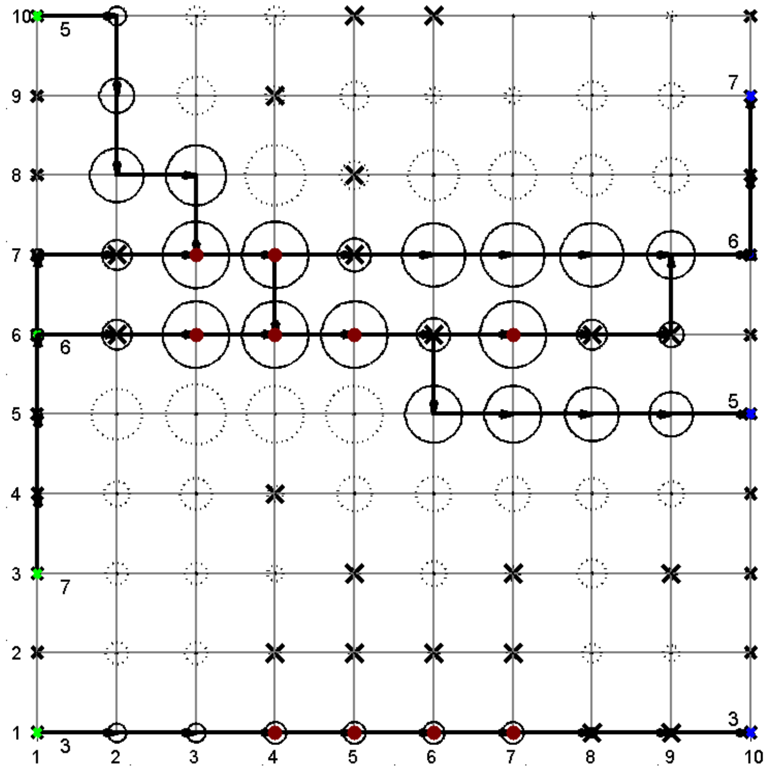


Figure 5-4 Snapshot of node congestion level by using shortest path routing metrics

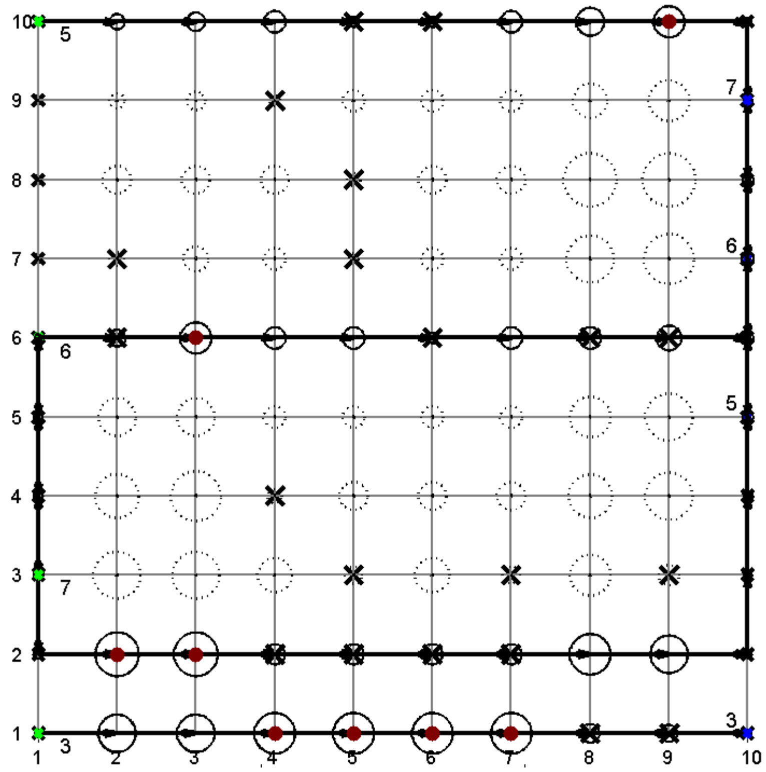


Figure 5-5 Snapshot of node congestion level by using BAR

Earlier, we discussed how the bottleneck capacity of nodes can jeopardize the performance not only on a specific traffic flow, but also the capacity of the whole ad hoc network. It is crucial to try and reduce the number of bottlenecks and increase the bottleneck capacities. Figure 5-6 shows the benefit of reducing the bottlenecks using BAR routing metrics. In this figure, the horizontal dot line indicates the *90th* percentile of each figure. Due to the bottleneck aware feature, *90%* of the bottlenecks have a node virtual capacity value of about *110* kbps (as the point on the x-axis where a vertical line intersects the BAR curve on *90th* percentile), about *75* kbps (as the point on the x-axis where a vertical line intersects the CAR curve on *90th* percentile) and about *63* kbps (as the point on the x-axis where a horizontal line intersects the SH curve on *90th* percentile) by using BAR, CBR and SH respectively. At this percentile, BAR shows a significant improvement on increasing bottleneck capacity by *31.8%* and *42.7%* higher than SH and CBR respectively.

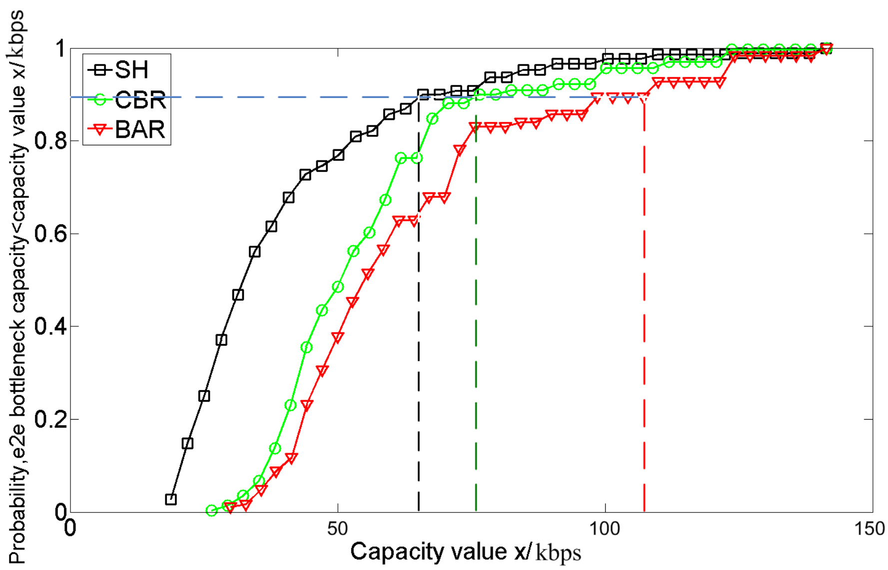


Figure 5-6 CDF of long-term end-to-end bottleneck capacity with different routing metrics

Figure 5-7 shows the sum of the bottleneck capacities on each active route against different traffic loads respectively. The minimum node/link capacity along a path is considered to the bottleneck and all routes only have a single bottleneck. The reason of using the total bottleneck capacity as a metric instead of the mean value is because the bottleneck capacity is the minimum capacity along the path and it is very small value. The bottleneck capacity depends on the network topology, node capacity, traffic pattern and routing metric. Although the routing metric is different, the other conditions are completely identical when applying different routing metrics. In Figure 5-7, bottleneck capacity is only determined by the applied routing metric, which cannot provide significant variations among different routing metrics if the mean bottleneck capacity was used. The total value can illustrate the maximum variation on the bottleneck capacity by comparing different routing metrics.

At light traffic load levels, the network has enough capacity for traffic relaying. Therefore, the BAR can route around bottleneck nodes by using extra hops or relaying without reducing the capacity of the network. It can be seen in Figure 5-7 for example that BAR improves the whole network bottleneck capacity by *60%* and *14%* at an average traffic load of *4* traffic flows compared with SH and CBR respectively. At this traffic load, BAR can efficiently separate nodes or links into different classes. However, at heavy traffic load levels, CBR and especially BAR will reduce the network capacity due to their routing characteristic which attempts to avoid congested areas which could generate an extra relaying burden for the network. Moreover, the extra relaying competes for channel capacity not only with originated traffic but also with other relaying nodes. This competition for the channel capacity generates more bottleneck nodes and reduces the capacity of the network. We will show more details in the following chapters.

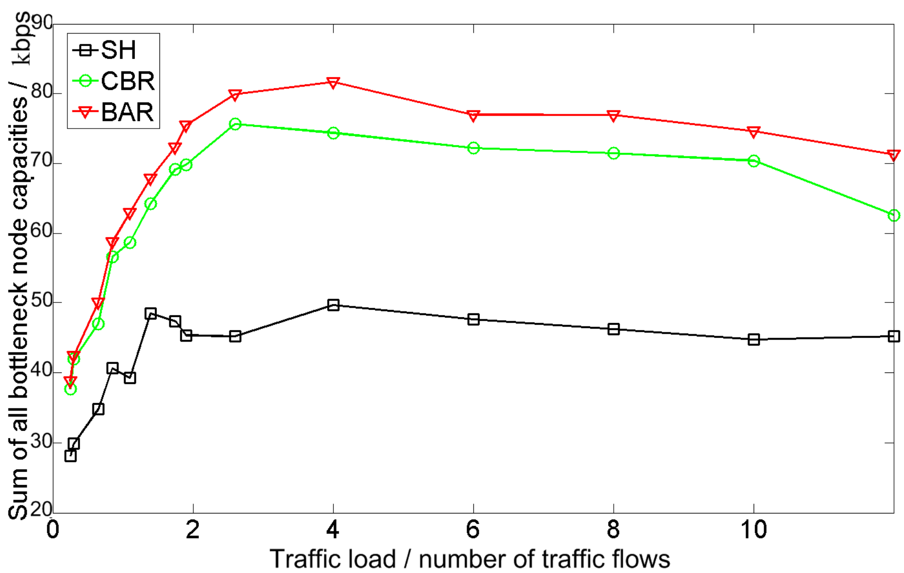


Figure 5-7 Summation of end-to-end bottleneck capacity against traffic loads

5.7 Conclusion

In this chapter, we proposed a novel routing metric design, Bottleneck-Aware Routing (BAR), which can improve the end-to-end bottleneck capacity in a relatively low traffic load network. The constraints of CBR and BAR have also been discussed.

BAR is considered to be more intelligent than shortest-path by hops (SH) and disturbance/inconvenience based routing (DIR) as it accounts for individual node/link capacity which is related to current traffic flows in its metric design. BAR not only takes individual node's interference and capacity into account like CBR but also is aware of the location of bottleneck nodes such that paths can intelligently pick the high capacity nodes to forward packets and also route around bottleneck nodes. Under low traffic loads, results show that BAR can improve end-to-end bottleneck capacity significantly compared with SH and CBR.

Chapter 6

6 Exploiting Cross-layer Design for Wireless Ad Hoc Networks

Contents

6.1 Introduction

One of the most important features of wireless ad hoc networks is their decentralized character, with nodes that can function as routers, fulfilling not only their own traffic demands, but also forwarding the packets of others (relaying). This feature helps node transmissions to reach their destination through multi-hop relaying. It also places constraints on ad hoc networks, due to the competition for the limited frequency spectrum between relaying and originated traffic as well as between relaying traffic from different sources. In addition, this relaying burden on the network reduces per node throughput, as shown in [12], the throughput per node shrinks in scaled length as $O(1/\sqrt{n})$. The relaying burden is generated since nodes have to spend their transmission time sending the data of other nodes [68]. The relaying burden on intermediate nodes has been considered as one of the main capacity constraints in wireless ad hoc networks. Therefore, unnecessary relaying/hops should be minimised for route selection.

In wireless ad hoc networks, the selection of suitable intermediate nodes for relaying traffic is crucial and will influence future traffic. The traditional wireless ad hoc network routing metric is shortest path by hops (SH), which selects routes using the criterion of minimum hop count. This is the simplest routing metric and it has the lowest relaying burden impact on the network. However, SH is not aware of any network conditions such as capacity, energy consumption, throughput etc and it tends to cause congestion problems by leading traffic flows to specific locations. Other routing metrics e.g. DIR, BAR and CBR as shown in the previous chapters, can take interference, bottleneck and capacity into their routing metric designs in order to move routes from a congested area to one less crowded. However, the relaying burden rises due to an increased number of hops around the network. Those routing metrics reduce the network capacity even further in the scenario where channels are inadequate to satisfy the relatively high traffic demand as they generate extra hops. Unnecessary relaying hops creates more severe competition on the limited frequency spectrum and results in producing more bottlenecks.

Since it is a big challenge for wireless ad hoc routing metric design to solve the trade-off problem between relaying burden and bottlenecks, in this chapter we will introduce a cross-layer design to minimise the relaying impact on the network without deteriorating the end-to-end quality of service. The cross-layer scheme is associated with a novel routing metric design ‘Cognitive Greedy-Backhaul (CGB)’ with a channel assignment scheme. It aims to create cognitive backhaul links which can reduce the relaying burden and alleviate the bottleneck problem. In this thesis, we refer to backhaul links as links with higher capacities and which are subject to a high traffic demand due to their important geographical locations. In other words, backhaul links are created in congested areas with higher capacity.

Unlike other routing metrics that exploit the spatial-temporal diversity to improve the spatial reuse/capacity of the network, CGB forces routes to go through nodes/links/areas with naturally important geographical locations which generate a relatively low relaying impact on the network. These crowded links can provide extra capacity if an appropriate channel assignment scheme is applied. In other words, a bottleneck problem can be alleviated if we can assign more channels/capacities intelligently to the places where they are needed. A couple of simple channel assignment schemes are initially applied to understand how the cross-layer design and CGB function in wireless ad hoc networks.

This chapter is structured as follows. Section 6.2 and 6.3 outline the cognitive greedy-backhaul routing and simple channel assignment schemes respectively to be used in the cross-layer design. In section 6.4, we introduce our network model. In addition, we compare the proposed CGB routing metric with shortest path by hops (SH) and Capacity-Based Routing (CBR) by presenting simulation results in section 6.5. Finally, the conclusions are drawn in section 6.6.

6.2 Cognitive Greedy-backhaul Routing

CGB aims to create cognitive backhaul links by exploring network conditions, traffic demand and channel usage. It requires the routing metric to exploit environmental information sensed by nodes and for them to adapt their weighting factors to indirectly improve the end-to-end performance of the whole network.

In this chapter, multiple channels are used in the network instead of the single channel scenario applied in previous chapters, and links can occupy more than *1* channel for their data transmission. In this thesis, the number of channels required for a link is determined by the number of different originated traffic flows flowing through the link. This is to make sure wireless ad hoc network capacity can still be maintained for nodes/links with important locations to avoid becoming bottlenecks when a suitable channel assignment scheme is applied. For example, Figure 6-1 shows that link ℓ requires *3* channels to transmit data from source node S1, S2 and S3 without becoming a bottleneck link. Thus, we say that link ℓ has the channel utilization level of *3* as three different originated traffic flows (from S1, S2 and S3) are required to go through the link. To enable transmissions to be simultaneously operated not only between the intermediate links on the same flow path but also between links on a different flow path, a good channel assignment scheme has to be applied with CGB to avoid intra-flow and inter-flow interference.

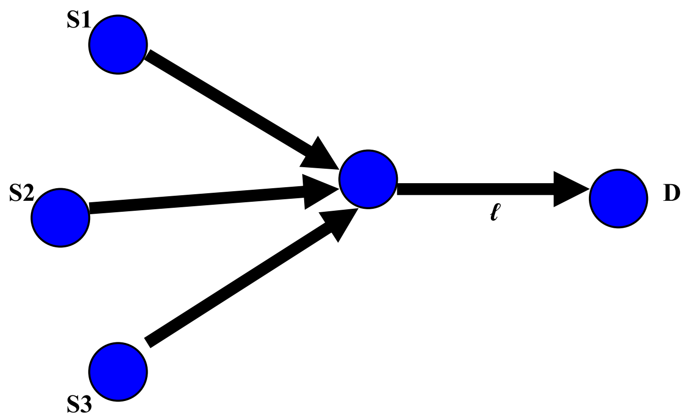


Figure 6-1 Channel usage example

Earlier, we commented that one of the main capacity constraints of wireless ad hoc networks is caused by the relaying burden. From a wireless ad hoc routing perspective, the extra relaying burden is generated from unnecessary relay hops. Traditional wireless ad hoc routing metrics cannot solve this problem. Cognitive greedy-backhaul routing (CGB) selects links based on their utilization level, which we define as the number of source-to-destination pairs that are required to go through the link. CGB relays traffic flow through crowded links due to their important geographical location. Those routes are constructed based on their important geographical location which leads to a minimum hop scheme from source to destination. With a proper channel assignment scheme, additional capacity can be allocated to those crowded links and backhaul links can be established. The relaying burden and bottlenecks are improved by attracting traffic through those backhaul links.

Figure 6-2 illustrates how CGB functions. Initially, CGB selects the route as the shortest path by hops (SH) in Figure 6-2 (a). Based on the traffic requirement and geographic location, heavily used nodes/links can be distinguished. Then, those links attract more traffic flow due to their lower weight values. Link capacity is maintained by assigning more channels to fulfil different traffic flows as shown in Figure 6-2 (b). Finally, more upcoming traffic will flow through the backhaul links due to their lower weight value as shown in Figure 6-2 (c). In contrast, some routing metric designs have been proposed to overcome the bottleneck problem by diverting around crowded areas such as a hotspot mitigation protocol (HMP) [66] and bottleneck-aware routing (BAR). Those diverting routes increase the relaying burden due to the longer distance/greater number of hops taken as they route around congested areas or bottleneck nodes/links. Therefore, in the scenario where traffic load is relatively high with respect to channel capacity, those routing metrics potentially create even more bottlenecks and congested areas.

CGB forwards nodes with a high channel utilization level (number of channels occupied). Here the link weight of CGB is defined as:

$$w_{ij} = \frac{1}{U_{ij}}, U_{ij} \le |P|, \forall i, j \in V \tag{6.1}$$

U_{ij} indicates the utilization level of the link ij which is equal to the number of end-to-end traffic flows through the link. In other words, U_{ij} also equals the number of channels that are required for link ij due to the assumption we made that the number of channels required for a link is equal to the number of different end-to-end traffic flows through the link in order to avoid the bottleneck node problem. P and $|P|$ are the set that contains the channels, and the number of channels that can be used in the network, respectively.

The link weight is positive which proves the routing metric is monotonic. In addition, the link weight is determined by the number of traffic flows through the link at the previous event. Therefore, the subsequent choice of path will not affect the weight value of the predecessor path as the number of traffic flows through the object link is already determined at the last event. This shows the CGB routing metric is isotonic. More details about routing isotonicity and monotonicity can be found back in Chapter 2.

CGB prefers to pick nodes/links which have more occupied channels. This means the higher the channel utilization level of a node/link, the more likely it is that CGB will select it for future traffic flows, thus cognitive backhaul links are established. CGB builds cognitive backhaul links by exploring the traffic conditions and important geographic location of nodes; it can occupy more channels, delivering higher capacity where a high level of traffic is required. Therefore the bottleneck problem is reduced by using a backhaul which can obtain more capacity if needed.

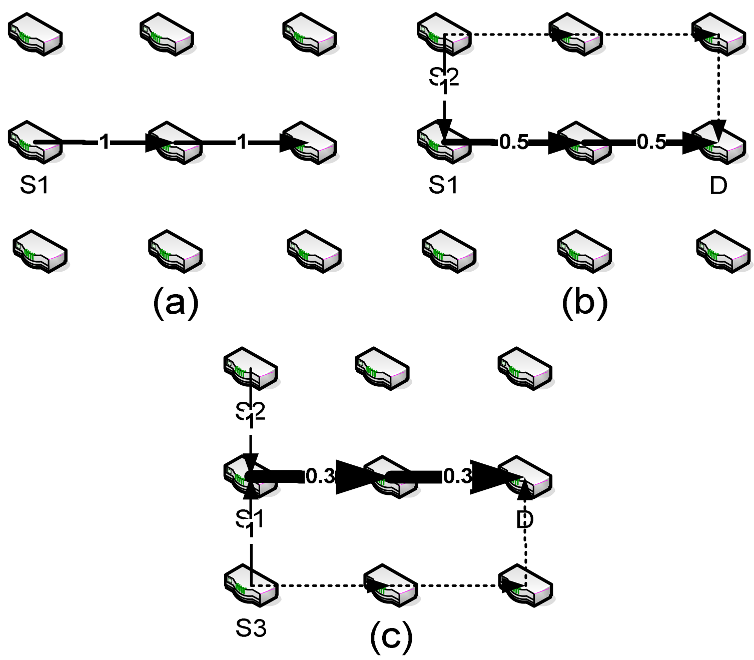


Figure 6-2 Shows how CGB performs (a) initial function as SH by same weight value of 1, (b) weight value reduces due to the usage, (c) backhaul links established due to the important geographical locations; solid arrows indicate CGB path; dotted arrows show the possible route selection by shortest path

6.3 Simple Channel Assignment Scheme

To illustrate the benefits of using the cognitive greedy-backhaul algorithm, the network needs to operate in a multi-channel environment. Therefore we apply two simple channel assignment schemes to start with to understand how this cross-layer design can achieve end-to-end goals in wireless ad hoc networks. More advanced channel assignment schemes will be applied with CGB to analyse the cross-layer design impact it will have on the practical wireless ad hoc network scenario in the next chapter.

The cognitive greedy-backhaul routing metric has the ability to force traffic flows to form concentrated backhaul links. In order to reduce the bottleneck problem, we need to consider the cross-layer design and assign more channels (capacity) to the backhaul links as needed. Due to the focus on routing metric design in this chapter, we therefore introduce two relatively basic channel assignment schemes for the benefit of illustrating this novel routing metric design. To simplify the channel assignment scheme in this chapter, the same channel is assigned to an entire end-to-end traffic flow. In other words, assuming an appropriate channel assignment scheme is used and there are sufficient channels, we only need to consider the intra-flow rather than inter-flow interference and resource sharing. In the case where there are insufficient channels for this to occur, capacities are equally divided by intra-flow and inter-flow interference. The point of illustrating these two channel assignment schemes is to show how the cognitive greedy-backhaul routing metric can performs better with a better channel assignment scheme than a poor one. In the next chapter, we will elaborate on how well CGB can be associated with a reinforcement learning based channel assignment scheme.

6.3.1 Random Scheme

A random channel assignment scheme assigns channels from a spectrum pool randomly to a new traffic flow without considering spatial reuse and fairness. We assign a random channel $x_i \in \{1,2,3,.., p\}$ to each new end-to-end traffic flow, where p is the number of channels available in the network.

6.3.2 Quasi-fair Scheme

The quasi-fair channel assignment scheme assigns channels from a spectrum pool corresponding to current channel utilization in the network. The least utilized channels (u_p) are selected for new traffic flows that arrive in the network rather than using the channels that have already been allocated to the existing traffic flows. Each source node sends HELLO packets that include the channel it occupies periodically on all channels. Nodes receive the HELLO packets from source nodes and can determine the utilized value of each channel and make a decision about which channel is assigned in the link layer. For example, if there are *3* channels ($x_i \in \{1,2,3\}$) available and *5* concurrent traffic flows in the network. If channels *1*, *2* and *3* are assigned to traffic flows twice ($u_1 = 2$), twice ($u_2 = 2$) and once ($u_3 = 1$) respectively, then channel *3* will be allocated to the *6th* concurrent traffic flow. This is because u_3 is the lowest utilized value compared with the other channels. The quasi-fair scheme is more 'intelligent' than the random scheme as it takes current channel utilization into account. It is a centralised channel assignment scheme which operates in an opposite way to a distributed scheme. This shows that with a better channel assignment scheme, the cross-layer design can deliver better results. In the next chapter, channels are assigned in a distributed way for all channel assignment schemes.

6.4 Network Model

In this section, we introduce our network model which includes the main performance factors: end-to-end throughput and available capacity.

6.4.1 Capacity and Throughput

In contrast to the capacity model we introduced in the previous chapter, we use a multi-channel model to examine how well the greedy routing metric can cope in a multi-channel scenario. The available capacity (C_a) is determined by the summation of the remaining capacity (C_r) on each channel. We assume nodes have the same transmit power, therefore the remaining capacity (C_r) of channel k for the objective node j is only defined by the intra-flow and inter-flow interference on channel k within the interference range of node j and maximum channel capacity (C_{k_m}) is:

$$C_{r,j\_k} = \frac{C_{k\_m}}{CL_{j\_k} + 1}, \forall j \in V, \forall k \in P \tag{6.2}$$

Where V and P are the set of nodes and channels in the network respectively. C_{k_m} is the maximum capacity that can be achieved by channel k, which is *20* Mbit/s in this chapter for all channels. CL_{j_k} is the congestion level of node j on channel k. The congestion level of node j on channel k is defined as:

$$CL_{j\_k} = \sum_{i\_j=0}^{NI_j} R_{i\_j}, \forall j \in V \tag{6.3}$$

Where NI_j is the number of nodes within the interference range of node j, and R_{i_j} is the number of routes going through node i_j, which is one of the interferers of node j, using channel k. R_{0_j} indicates the number of routes going through the node of interest. For example, we can see from Figure 6-3 that the congestion level of objective node N_0 by using channel *3* is *6* active links which includes all intra-flow and inter-flow interference. This indicates that each activated link which uses the same channel shares the same amount of bandwidth to fulfil their transmissions.

The available capacity of node j is defined as:

$$C_{a\_j} = \sum_{r\_j=1}^{|P|} C_{r\_j}, \forall j \in V \tag{6.4}$$

Where $|P|$ is the number of channels that can be used for the network, C_{r_j} is the remaining capacity of node j by using channel r_j which is one of the channels in the network. In Figure 6-3, there are three channels in the network. The remaining capacities of node N_0 for channel *1*, *2* and *3* are *5* Mbps, *4* Mbps and *2.5* Mbps respectively. Thus the available capacity of node N_0 is *11.5* Mbps. This implies that the route has to share the bandwidth not only with routes going through the node of interest, but also with the routes going through the interferers of the objective node.

In the previous chapter, we investigated capacity based routing (CBR) in a single channel scenario. Here, available capacity-aware routing (AC) is proposed for multi-channel scenario. The available capacity-aware routing algorithm is based on the maximization of the accumulated impact available capacity has on multi-hop communication. The link weight of AC is defined as:

$$w_{ij} = \frac{1}{C_{a\_j}}, \forall i, j \in V \tag{6.5}$$

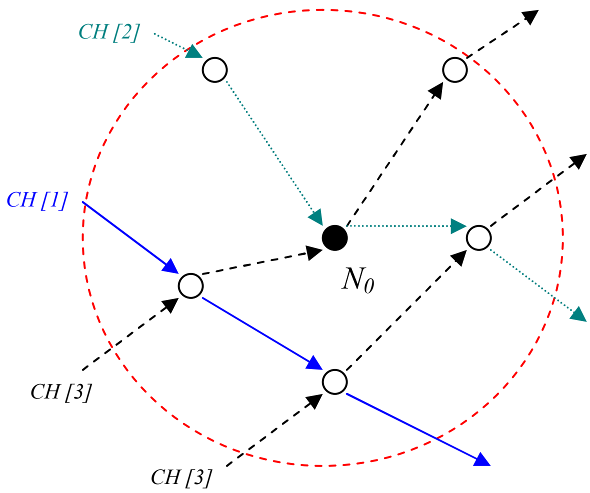


Figure 6-3 Example of traffic flows through the network

The throughput of node j is defined as:

$$S_j = \eta \sum_{ch\_k=1}^{NC} \frac{C_{ch\_k,m}}{CL_{ch\_k} + 1}, \forall j \in V \tag{6.6}$$

Where η indicates a MAC efficiency factor; NC is the number of channels that have been utilised by node j; $C_{ch\_k,m}$ is the maximum capacity of channel ch_k and CL_{ch_k} is the congestion level of node j on channel ch_k.

Evaluating end-to-end bottleneck throughput is our main method of evaluating the performance of the combined routing metrics and channel assignment schemes. It is constrained by the minimum throughput value along the path, i.e. it occurs when the upstream node of the bottleneck node injects more packets into the link than the bottleneck node can forward. End-to-end delay increases as packets get stuck at the bottleneck and the throughput reduces as these packets are eventually blocked by the congested node.

6.4.2 Parameters

In this chapter, we assume a wireless ad hoc network where nodes are in a fixed location without mobility. The aforementioned routing metrics will be examined in a randomly located node environment. There are *99* source nodes and *1* sink node, located randomly in the network. The key parameters are shown in Table 6-1. This is a fully connected scenario. We assume routes do not change during their life-time once they are established. This is convenient for nodes to sense the state of the network and to reduce the route oscillation problem [67].

Key parameters	**Value**
Network size	40×40 m^2
Number of nodes	*100*
Number of source nodes	*99*
Number of sink node	*1*
Number of channels	*10*
Node's transmission range	*7* m
Node's interference range	*14* m
Maximum channel capacity	*20* Mbps
Mean duration of each connection per source node	*0.2* seconds
Inter-arrival distribution range per source node	*0.25* to *6* arrivals/second

Table 6-1 Parameter values used in the example scenario

All traffic originates at source nodes. Each source node generates *5* route connections. This is a call based traffic model as end-to-end traffic flow arrival (ON) and departure (OFF) follow an exponential distribution. The routing metrics are examined on a time event basis. An event occurs when an end-to-end flow is established or deactivated in the network.

6.5 Results

In this section, we examine the effectiveness of the different routing mechanisms proposed. We assume a perfect MAC which has an efficiency factor of *1* in equation (6.6). Figure 6-4 shows the cumulative distribution function of the average maximum number of channels per flow at a traffic load of *20* traffic flows using different routing metrics and channel assignment schemes. There are *10* channels available in the network. From Figure 6-2, the shortest path by hops (SH_{QF}) and available capacity-aware routing (AC_{QF}) of using quasi-fair channel assignment scheme both have *45%* of the total traffic through a maximum number of *9* channels per flow. This amount of traffic is gathered to congested links due to their important locations. Comparing with SH_{QF} and AC_{QF}, we can see that there are about *72%* of total flows which have a maximum number of channels greater than *9* on an end-to-end basis by using a cognitive greedy-backhaul routing metric associated with quasi-fair channel assignment (CGB_{QF}). This additional *27%* of total traffic flows are encouraged to go through cognitive backhaul links by using CGB_{QF}. As aforementioned, the link weight of CGB is determined by the number of channels assigned to it. The more channels allocated to a link, the lower the weight associated with it. The advantage of using CGB is forcing local traffic to go through nearby backhaul links in a concentrated rather than a distributed manner, which can reduce the total interference and relaying burdens caused by the increased number of hops around the network. In addition, CGB relays traffic by using fewer numbers of nodes as the upcoming traffic prefers to pick a node with a higher channel utilization level. This can save network energy by relaying traffic through nodes which have been already activated rather than through asleep/inactive nodes. More details will be shown in the next chapter.

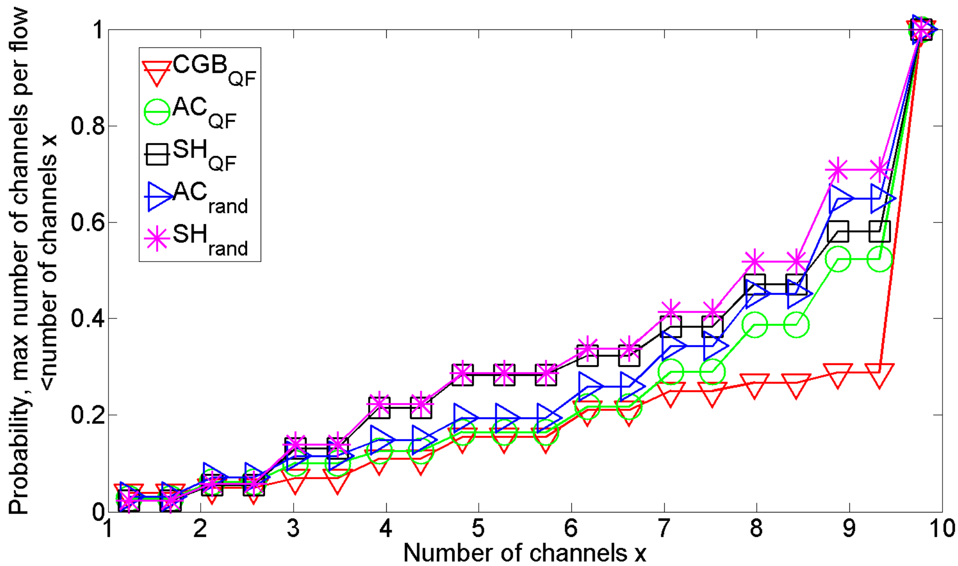


Figure 6-4 CDF of the average maximum number of channels per flow

Figure 6-5 and Figure 6-6 illustrate the end-to-end bottleneck throughput versus different traffic loads and number of channels respectively. In Figure 6-5, there are *3* channels available in the network and we can see that the channel assignment scheme plays a significant role for the end-to-end bottleneck throughput at a low level of traffic load. Due to the intra-flow and inter-flow interference and the limited number of channels available in the network, it is reasonable that the bottleneck throughput value remains low. In Figure 6-5 where traffic load is quite low, the cognitive greedy backhaul (CGB), available capacity-aware (AC) and shortest path by hops routing metrics have similar end-to-end throughput using the same channel assignment scheme. This is because channel capacities are adequate to accomplish the traffic demand without causing too many bottleneck links. The disadvantage of using the random channel assignment scheme by routing metrics AC and SH (referred to AC_{rand} and SH_{rand} respectively) is that it does not have any knowledge of current network conditions. The same channel can be assigned to routes within a close distance which results interference to each other (inter-flow interference). End-to-end bottleneck throughput cannot show the great advantage of using different routing metrics due to the limited number of channels available in the network at the higher level of traffic load. However, CGB_{QF} improves the end-to-end bottleneck throughput by around *25%* compared with SH_{rand} at a traffic load of *4* traffic flows. Although the MAC layer design is the main factor to improve the network performance (e.g. throughput), it is encourages us to use a better routing metric associated with the MAC design to maximize network performance.

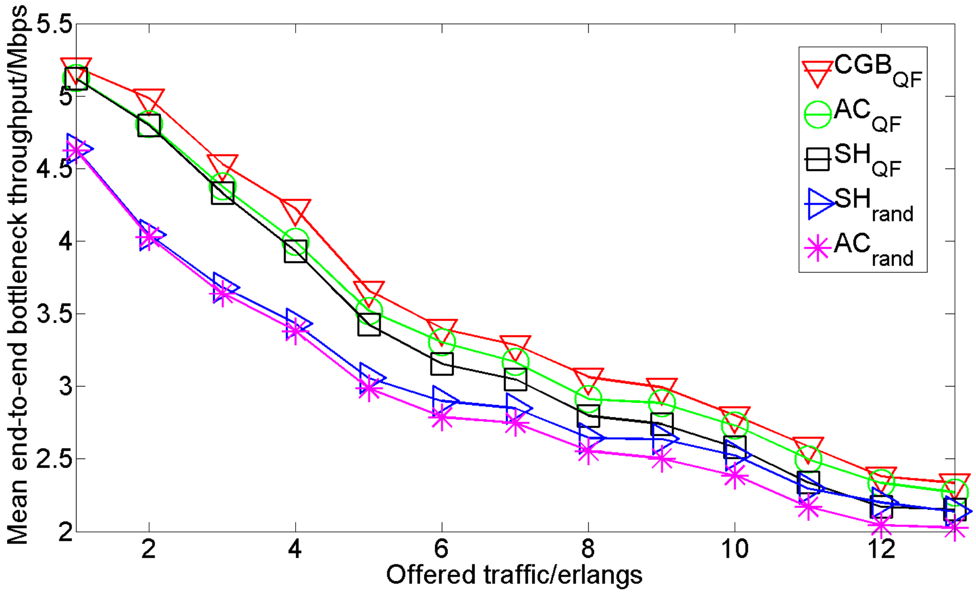


Figure 6-5 Mean end-to-end bottleneck throughput versus traffic load

Figure 6-6 shows the dramatic difference between the different channel assignment schemes as a function of the number of channels. AC_{QF} selects routes to maximise the total end-to-end capacity value. This can increase the relaying burden by hopping around to find the high capacity links/nodes. Due to the lack of cognition of the network environment, SH_{QF} selects routes depending on their location and can potentially create bottlenecks. CGB_{QF} reduces the relaying burden by routing traffic flows through common cognitive backhaul links and as traffic is forced to flow through those backhaul links, interference is limited to the backhaul areas. The rest of the nodes in the network can therefore fulfill future traffic demands by minimising interference around them. Although this work has focused on the network layer rather than the MAC layer design, due to the cross-layer design concept of the cognitive greedy-backhaul routing metric, CGB benefits from an appropriate channel assignment scheme. The main concept of CGB is to occupy more channels for the links which have the potential to become bottlenecks due to their geographical importance in order to create backhaul links. In Figure 6-6, we can see that CGB tends to perform better at end-to-end bottleneck throughput compared with the others as the number of channels is increased. The end-to-end bottleneck throughput increases about *30%* by using CGB_{QF} compared with

SH_{rand}. This is because backhaul links are generated by obtaining available channels in the network, since as the number of available channels increase, the capacity of the backhaul links is enhanced. Fundamentally, the reason for associating CGB with a suitable channel assignment scheme outperforming the other schemes is due to the routing metric behaviour of CGB which generates a relatively low relaying burden impact due to the shortest path approach, as well as the channel assignment scheme that can provide the required bandwidth for those crowded links which are attracted by the CGB routing metric, in order to avoid deteriorating end-to-end bottleneck nodes.

With a proper channel assignment scheme, CGB can perform even better as channel capacity can be provided to the backhaul links without causing intra-flow and inter-flow interference. The quasi-fair channel assignment scheme is not ideal as the scheme cannot solve intra-flow interference. Therefore, we will provide an advanced channel assignment scheme and a more practical network environment in the next chapter.

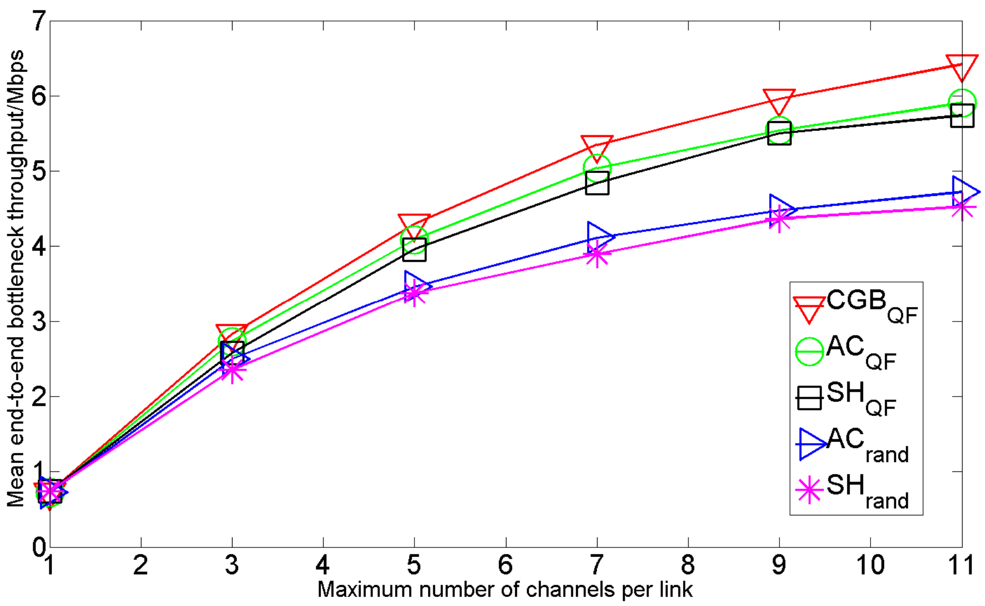


Figure 6-6 Mean end-to-end bottleneck throughput versus maximum number of channels per link

6.6 Conclusions

We have proposed a cognitive greedy-backhaul routing metric (CGB) which can force local traffic through nodes with high channel utilization levels due to their important geographical location. These routes create a relatively low relaying burden impact on the network. By combining with a good channel assignment scheme, additional capacity can be provided for the crowded links to avoid bottleneck problem. This cross-layer design is able to mitigate the bottleneck problem without diminishing the capacity of a wireless ad hoc network.

Chapter 7

7 Cross-layer Design Impact for CGB

Contents

7.1 Introduction

Minimizing energy consumption without deteriorating network capacity of a network is an important challenge for routing metric design in wireless ad hoc networks. The previous chapter shows how wireless ad hoc networks can be made more scalable by using cognitive-greedy backhaul (CGB) routing due to the relatively low relaying burden they generate. Unlike chapter 6, here we will show an improved approach by combining a reinforcement learning based channel assignment scheme (RLCAS) with CGB in a more typical network environment. With additional channels assigned to those crowded links, a trunked backhaul link can be established as CGB prefers to relay traffic through nodes that are currently utilized. Backhaul links are introduced in this paper as links with higher capacities that are subject to a high traffic demand due to their important geographical locations. Additionally, a proper cross-layer design (CGB with a suitable channel assignment scheme) can relay traffic flows by using a limited number of nodes without deteriorating network capacity. Therefore network energy consumption can also be reduced by using fewer nodes/links for traffic relaying, with other nodes put into sleep mode. The subject of this chapter is to propose a cross-layer design that combines the Cognitive Greedy-Backhaul (CGB) routing metric with reinforcement learning based channel assignment (RLCAS) to improve the energy consumption without diminishing other QoS parameters such as throughput and delay.

The content of this chapter is organised as follows. First we illustrate a more practical network environment for the proposed cross-layer design. Next we discuss the concept of reinforcement learning and a sensing based channel assignment scheme, and explain how RLCAS can be associated with CGB. Then, the details of different schemes combining varying routing metrics with RLCAS are given. This is followed by thorough and comparative performance evaluations of how each scheme impacts on different network parameters in terms of network energy consumption, delay, throughput and dropping probability. Finally, conclusions are drawn.

7.2 Network Model

In previous chapters, our routing metrics are examined in a relatively ideal network environment due to the assumptions we made. Here, we examine the effectiveness of the cross-layer design in a network environment by including a path loss model, more practical interference model and energy model.

7.2.1 Network Environment

As in previous chapters, we have *100* nodes which are deployed in a square network of *550* m by *550* m without mobility. The network is implemented in the *2.4* GHz frequency band and the maximum transmission range of each node is identical and fixed to the value of *100* meters [69]. This is a fully connected scenario. There is no connection between nodes that are beyond *100* meters away from each other. Routes do not change during their life-time once they are established. This is convenient for nodes to sense the states of the network and to reduce the route oscillation problem [67]. The key network parameters are shown in Table 7-1. We assume there are *100* orthogonal channels available, so that adjacent channel interference is not considered in this thesis.

7.2.2 Path Loss Model

In this chapter, we use a path loss model to calculate path loss with respect to distance between transmitter and receiver as well as the system frequency it operates at. The WINNER path loss models of B5a scenario [70] is selected as its rooftop-to-rooftop scenario is similar to our network scenario which is a homogenous scenario with a fixed node location. In addition, the model also support multi-hop networks. The path-loss does not depend significantly on the antenna heights as B5a is a line-of-sight stationary feeder rooftop-to-rooftop scenario where the connection is almost identical to free space. X can be neglected in equation (7.1) as it is an optional, environment-specific factor such as wall attenuation.

Key parameters	**Value**
Network size	*550* × *550* m^2
Number of nodes	*100*
Number of source nodes	*99*
Number of sink nodes	*1*
Number of channels	*100*
Node transmission range (r)	*100* m
File length	*1* Mb
Maximum channel capacity	*9* Mbps
Arrival rate per source node	*0.01* arrivals/second
Power consumed for Tx/Rx modes (P_T, P_R) [71]	*100*, *50* (mW)
Power consumed for sleep mode in best/ worst case scenario (P_S)	*0*, *50* (mW)
Path loss model	WINNER II B5a [70]

Table 7-1 Parameter values used in the network

The path loss models in [70] are typically of the form of the following equation:

$$PL[dB] = A\log_{10}(d[m]) + B + C\log_{10}\left(\frac{f_c[GHz]}{5.0}\right) + X \tag{7.1}$$

Where d is the distance between the transmitter and the receiver in m, f_c is the system frequency in GHz, the parameter A includes the path-loss exponent, parameter B is the intercept, and C describes the path loss frequency dependence. Those parameters can be found in Table 7-2. In this path loss model, the shadow fading is not considered as the model is transmission pair distance and frequency dependent only. h_{BS} and h_{RS} are the effective base station antenna height and the relay antenna height respectively [70]. The signal in B5a is assumed to travel between the antennas in line of sight.

Scenario	Path Loss [dB]	Shadow fading std [dB]	Applicability range, antenna height default values
B5a LOS	$A = 23.5$, $B = 42.5$, $C = 20$	$\sigma = 4$	30 m $< d < 8$ km $h_{BS} = 25$ m, $h_{RS} = 25$ m

Table 7-2 Path loss models parameters for B5a scenario

7.2.3 Interference Model

Unlike the previous chapters where the interference model is based on a fixed circle, we apply a more practical interference model here which is due to the signal to interference plus noise ratio (SINR). In this chapter, a transmission fails due to the interference it suffers from other transmitters on the same channel if the SINR value of the receiver is below the SINR threshold.

Here is the equation to calculate the SINR at the receiver *Xr*.

$$SINR_{Xr} = \frac{P_r}{N + I_r} \tag{7.2}$$

Where P_r indicates the received power sent from node *Xs*, I_r is the total interference received by the receiver *Xr*, *N* is the noise power which is *7.5e-14*W (*-131*dBW). These parameters are shown in Table 7-3.

Parameter	Default Value
Transmitter / Receiver height	*25* m
Antenna Efficiency	*100%*
Noise power	*-131* dBW
Channel bandwidth	*20* MHz
System frequency	*2.4* GHz
Sensing threshold	*-93* dB
SINR threshold	*7.6* dB

Table 7-3 Parameters for the path loss model

$$P_r[dB] = P_T[dB] - PL[dB] \tag{7.3}$$

Where P_T is the transmit power of X_S which is *-10* dBW (*100* mW) as shown in Table 7-1.

A transmission is considered to be interfered with if the receiver SINR drops below the SINR threshold. Our SINR threshold value is defined as *7.6* dB in this chapter and the modulation parameters which we used to calculate the SINR threshold are in Table 7-4 [72].

Modulation Parameter	**QPSK**
Code Rate [1]	*0.87*
Bit Rate (Mbit/s) [2]	*27.84*
BW Efficiency (η - bits/s/Hz) [3]	*1.392*
Eb/No (dB) [1]	*6.2*
SINR (dB) [4]	*7.6*

Table 7-4 Modulation and coding parameters used to determine capacity and SNR

[1] Code rate = *0.87* (Reed-Solomon code (*255*,*223*) using hard decoding), assumes BER 10^{-5}, Eb/No is *6.2*dB in [72].

[2] Channel bandwidth = *20* MHz (roll-off factor *0.25*), therefore max symbol rate = $20/(1+0.25) = 16$ Msymbols/sec). Bit rate = $16\times 2\times 0.87 = 27.84$ Mbit/s

[3] BW Efficiency = Bit Rate / channel bandwidth = *1.392* bits/s/Hz

[4] SNR = $\eta\times$Eb/No = 1.392×4.17(*6.2*dB) = *5.8*(*7.6*dB)

The parameters in Table 7-3 and Table 7-4 (e.g. BER and noise power etc.) are typical values obtained from the literature, with the SINR level derived assuming an Additive White Gaussian Noise channel. Each desirable bit error rate has a corresponding SINR value, and it is the fact that we have a threshold(s) that governs behaviour. For example, the bit rate can be changed by changing the modulation scheme; different communication services (e.g. voice, video) may require a different BER. Different noise environments, e.g. Rayleigh or Ricean, will also affect the required SINR values, but can be modelled by an additional SINR margin for a particular quality of service, but this level of detail is beyond the scope of this thesis, since the fundamental operation of the scheme will be relatively insensitive to specific SINR levels.

7.2.4 Traffic Model

In this chapter, our traffic model changes from a call-based model to a file/packet-based model in order to calculate delay by taking current network conditions and file/packet length into account. In previous chapters, our traffic model is an exponential ON/OFF model where the activation time is not related to any network conditions, e.g. channel capacity, co-channel interference etc. In the file/packet-based model, the time taken to finish the transmission on a file (delay) is related to some network factors such as file length, end-to-end bottleneck capacity, co-channel interference etc.

In this file/packet-based model, each source node generates *5* files and they have negative exponential distribution of interarrival times. The arrival rate of the files at each source node is *0.01* per second. Transmission of the end-to-end traffic flow is off once the file has been all transmitted from the source to the destination. The transmission (ON) time of a traffic flow at a certain period time depends on its end-to-end bottleneck capacity. The value of the capacity on a link is affected by the current channel assignment and interference model (more details can be found in section 7.3). Therefore, the total network file arrival rate is *0.99* per second as there are *99* source nodes. Routing metrics and channel assignment schemes are examined on an event basis. An event occurs when an end-to-end traffic flow is established or deactivated in the network.

7.2.5 Energy Model

Wireless nodes typically have a number of different power modes: transmitting, receiving and sleep. It is crucial to turn off the unnecessary intermediate relaying nodes in order to save energy [73]. Accordingly, relaying the traffic flow through those nodes which have already been activated (transmitting/receiving) is encouraged to reduce energy consumption by switching inactive nodes into sleep mode [74]. As shown in the last chapter, CGB routing selects a link based on its current utilization level which is the number of different originated traffic flows that are required to go through this link. Therefore, energy can be saved by relaying through those nodes which have been already activated. Intuitively, if we can assign more channels to links with higher traffic demand, we can maintain network capacity by solving the bottleneck link problem. A proper channel assignment scheme can allocate channels to those crowded links without causing co-channel interference.

Nodes are divided into *3* different power modes: transmit (Tx), receive (Rx) and sleep. In sleep mode, a node turns its radio off, so it can neither transmit nor receive, which is the most efficient way to save energy. In our scenario, the energy cost mainly depends on how long a node is activated. Poor cross-layer design may provide an unstable route selection or an inefficient approach towards the channel assignment scheme. There is a risk that a situation could occur where a channel is shared by many links, so that the channel capacity is reduced and shared by those links. It could result in a bottleneck problem which has the impact of increasing the delay. Consequently, the time taken for nodes in active mode (transmitting/receiving) is extended which consumes more energy in the network.

Our total network energy consumption is defined as below:

$$E_{total} = \sum_{e=1}^{|\tau|} E_e ; E_e \in \{E_1, E_2, E_3 ...... E_{|\tau|}\} \tag{7.4}$$

Where τ is defined as the set of events. E_e is the energy expenditure of the network since the last event which is determined by the power values for the different modes, number of nodes in each mode and time taken from previous event to the current event.

$$E_e = (N_T P_T + N_R P_R + N_S P_S) t_e \tag{7.5}$$

Where N_T is the number of nodes in transmit mode and P_T is the transmit power of each node. N_R is the number of nodes in receive mode and P_R is the power cost for receiving data. N_S is the number of nodes with their power off in sleep mode and P_S is the power consumed in sleep mode. t_e is the time taken from previous event to the current event. Here, we consider a best case scenario by assuming no power is consumed in the sleep mode and a worst case scenario where a node in sleep mode consumes as much power as a node in Rx mode. The power consumption of each mode is shown in Table 7-1.

7.3 Channel Assignment Schemes

To illustrate the benefits of using cross-layer design, we use two channel assignment schemes: a sensing based channel assignment scheme (SCAS) and a reinforcement learning based channel assignment scheme (RLCAS). The sensing based channel assignment scheme detects the interference level from the transmitter's perspective.

7.3.1 Sensing Based Channel Assignment Scheme

Firstly, we introduce a channel assignment scheme based on a spectrum sensing technique. The aim is to compare the cross-layer design of associating CGB with different channel assignment schemes.

Spectrum sensing is a major requirement in cognitive radio networks as it can detect unused radio spectrum and share it in most cases without harmful interference with other users. Moreover, spectrum sensing can be used to detect the presence of a primary user although this is not applicable for our network scenario. With the help of a spectrum sensing technique, radio spectrum can be allocated in a more efficient way for the RL based channel assignment scheme as it can initially limit channel selections.

The mechanism of the sensing based channel assignment scheme is illustrated here. Initially, the object transmitter detects the interference level it suffers on each channel. Then, the transmitter randomly selects a channel with its interference level below the sensing threshold value. If the transmitter senses that all of channels are occupied, in other words, the interference levels of the transmitter on each channel are above the sensing threshold, this connection will be blocked (if it is a new activated link which is trying to build a connection) or dropped (if the connection of the link already exists). The sensing threshold value is defined as the power received *100* m (transmission range) away from the transmitter:

$$\delta_s[dBW] = P_T[dBW] - PL[dBW] \tag{7.6}$$

Where δ_s represents the sensing threshold, P_T indicates transmitter power which is *20* dBm for all nodes. *PL (d = 100)* is the path loss at the distance *100* m away from the transmitter and it can be calculated based on equation (7.1) with parameters (*A*, *B* and *C*) are shown in Table 7-2. Consequently, the sensing threshold value is calculated as about *-93 dBW*.

7.3.2 Reinforcement Learning Based Channel Assignment Scheme

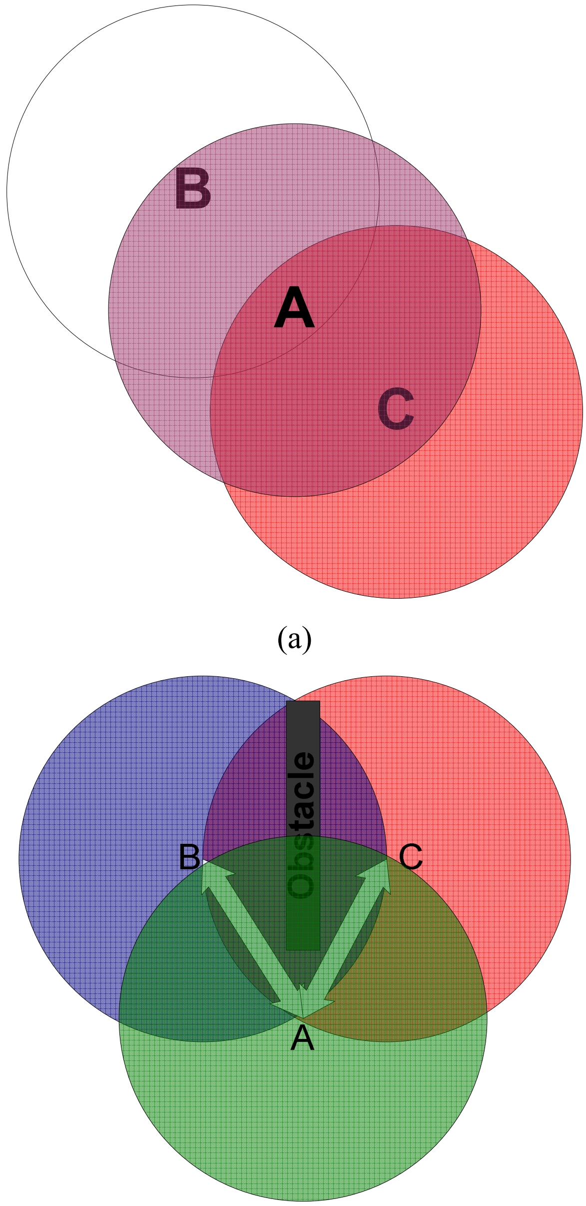
The sensing based channel assignment scheme cannot solve the hidden node problem [75] when allocating the spectrum as it can only detect the interference level from the transmitter's perspective.

Figure 7-1 shows the hidden node problem. Hidden nodes [75] in a wireless network refer to two nodes (Node B, C) that can be within range of the station (node A) but out of transmission range of each other, as shown in Figure 7-1 (a); or they (Node B ,C) are within range of each other but are separated by a physical obstacle as shown in Figure 7-1 (b), so that they can communicate with the destination but not to each other. In this thesis, our nodes are deployed on the roof-top scenario as shown in [70] where LOS stationary feeder is applied, therefore we only consider the hidden node problem as shown in Figure 7-1 (a) and exclude the hidden node problem caused by obstacles as shown in Figure 7-1 (b).

The existence of the hidden node problem significantly degrades the performance of sensing-based channel assignment schemes. For the two hidden nodes, each node is within communication range of the receiver node (node A), but the nodes cannot communicate with each other as they are out of transmission range of each other. Therefore, as they cannot sense the existence of each other, a collision will occur when they try to send packets simultaneously to the common receiver by using the same channel. The sensing-based channel assignment scheme can only detect the interference level suffered at the transmitter up to the transmission range as the sensing threshold value is defined by the path loss *100* m (transmission range of each node) away from the transmitter. Therefore, our sensing based channel assignment scheme suffers the hidden node problem which consequently leads to poor performance on throughput and delay.

In order to solve the hidden node problem with a distributed approach, we apply a reinforcement learning based channel assignment scheme (RLCAS) [76] which aims to allocate suitable channels to each activated link after a period of learning. This hidden node problem can be mitigated by a learning process, although a link cannot detect which links are interfering with it, at least it can be aware that there are other links using the same channel which causes its communication failure. Therefore, the link applies a punishment to the weight value on the channel so that it will not pick this channel due to the lower preference (as the weight value is low for this channel) in the future in order to avoid the potential channel collisions.

In this chapter, route and channel selection are based on a decentralized approach where users obtain information locally in a distributed manner. Machine learning has been suggested as an efficient way to assign spectrum in a decentralized approach. The learning engine of a cognitive cycle is responsible for storing information based on experience to aid future decisions by the reasoning engine [77]. Reinforcement learning is an area of machine learning which is concerned with how an agent interacts with an unpredictable environment by selecting different actions and receiving rewards accordingly [78]. Therefore, it is suitable for a multi-channel scenario that assigns channels in a more efficient and distributed way due to its emphasis on individual learning from direct interactions with the environment. An important challenge when applying machine learning for a spectrum assignment scheme is that the environment may change faster than the learning engine can deal with. Indeed, in a fast changing network environment, changes such as random traffic patterns, route/link alterations, etc can result in an out of date knowledge base in the learning engine. In multi-hop wireless networks, a poor routing strategy could increase the randomness of link selection exponentially compared with the single transceiver link scenario [79]. Therefore, cognitive routing with an efficient channel assignment scheme is desired to achieve end-to-end goals in wireless ad hoc networks.



(a)

(b)

Figure 7-1 Hidden node problem; the circles indicate the transmission range of the nodes

Figure 7-2 illustrates how the RLCAS works. Initially, to select a channel for link *l*, as shown in Figure 7-2 stage *1*, a node picks the highest weighted channel corresponding to link *l* from the channel weight table which has been build up through a learning process for each activated link from the beginning. The transmitter senses the interference level it suffers on channel *X*, and if the interference level is below the sensing threshold value (δ_s), which is defined in Equation (7.6), the channel X is considered to be available for link l to use. However, if the interference level of the transmitter on the channel X is above δ_s, the transmitter considers the highest weight channel (most preferable channel from past) is occupied by other users in the vicinity, so a punishment factor is applied to the channel for the link l in the channel weight table for future reference. Then, it will go back to stage *1* and will pick the next highest weight channel and repeat stage *2* and *3*, until it finds a channel to start its transmission; or there is no channel left to use from the transmitter perspective. The connection is then either blocked or dropped. Once blocking or dropping occurs, which indicates channels are heavily utilized around the link l, the node will retransmit the packet later (MAC scheme will be introduced later). If the transmitter senses that there is a channel to fulfil its transmission (from stage *3* to *4*), then the SINR at the receiver end of the link will be analyzed. Therefore, a reward or punishment is applied to the channel in the channel weight table depending on whether this transmission is successful or has failed respectively.

If the transmission has failed due to the SINR at the receiver (stage 7), this transmission has to share the channel equally with the interfered transmissions on a temporal basis (like a TDMA scheme). We assume a perfect time sharing scheme so that channel capacity is not wasted for a guard interval as transmission share the channel with highest possible efficiency. The perfect time sharing scheme will be introduced in the following section. This is to make sure our network QoS is influenced primarily by the different cross-layer design rather than the MAC scheme as the cross-layer design of combining Layer *3* with channel assignment scheme is the main focus of the thesis. Otherwise, in a heavy traffic scenario where our time sharing scheme is not applied, throughput and delay deteriorate significantly and they are mainly affected by the application of the MAC scheme. Consequently, throughput and delay could approach a trivial and infinite value respectively as dropped packets would retry their transmission which leads to a situation where the network is flooded with a large amount of retransmission overhead.

Reinforcement learning has been suggested as a suitable learning technique for a distributed spectrum sharing scenario as it emphases the individual learning process interacting with its local environment. Moreover, reinforcement learning is a computational approach to maximize some notion of long-term reward [80, 81]. Some research [82, 83] has concentrated on applying reinforcement learning to a channel assignment scheme in a single transceiver link scenario where routing is not used. In this chapter, we will also inspect the performance of the RLCAS in a multi-hop wireless networks, as well as its impact on routing metrics and vice versa.

The following equation is applied as an objective function to update the channel weight table in this chapter:

$$w_{ij\_c,t} = f_1 \cdot w_{ij\_c,t-1} + f_2 \tag{7.7}$$

Where $w_{ij\_c,t}$ indicates the weight value of link *ij* on channel *c* at current event time *t* and $w_{ij\_c,t-1}$ is the weight value of link *ij* on channel *c* at a previous event time *t-1*; f_1 and f_2 are the weight factors that can affect the current weight value of link *ij* on channel *c*. Table 7-5 demonstrates the weight factors value we used in this chapter.

f_1		f_2	
Reward	Punishment	Reward	Punishment
1	*1*	*+1*	*-1*

Table 7-5 Weighting factor values for f_1 and f_2.

After the initial learning process for each new activated link, the RLCAS is supposed to find suitable channels for each activated link with respect to their locations and network traffic patterns. Results will be demonstrated in the latter section of this chapter.

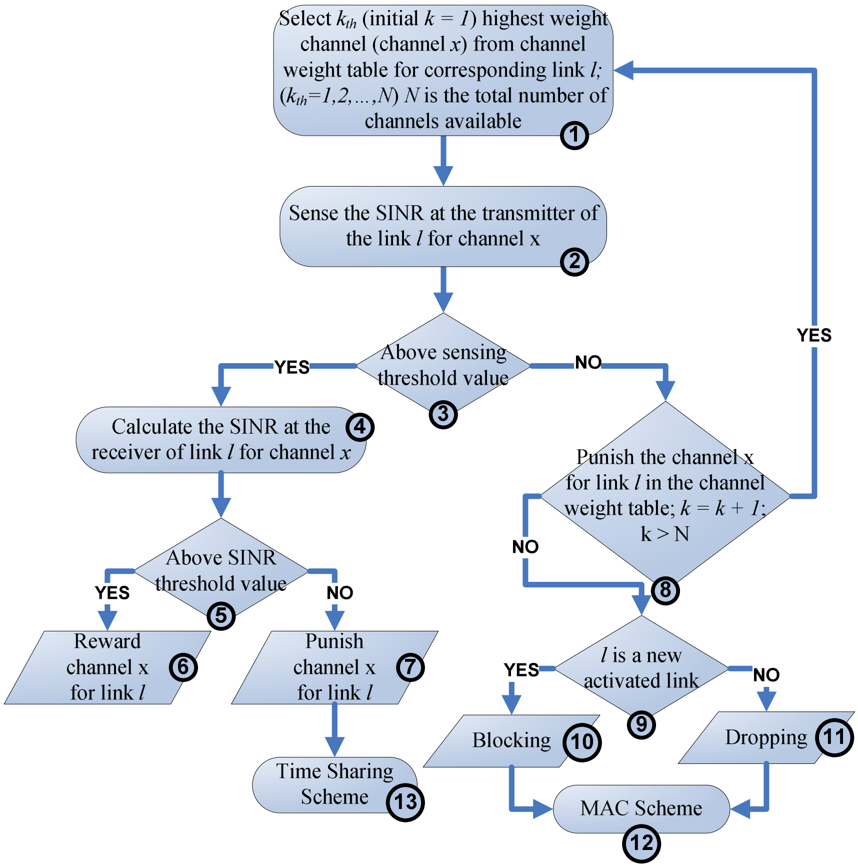


Figure 7-2 Flowchart of how RL based channel assignment function

7.3.3 Time Sharing and MAC Models

In this section, we will introduce details of the time sharing scheme and MAC scheme which we applied in our network model. Firstly, we will show the details of the time sharing scheme applied in this chapter, this will be followed by the MAC scheme.

Figure 7-3 illustrates the flowchart of the time sharing scheme. Notice that link l shares channel x only with those links that have impact/influence on their transmission rather than sharing them with all links that are using channel x. When the SINR of a link at the receiver is below the SINR threshold (shown in 7.2.3), then the link analyzes its interference separately to distinguish whether it can maintain its connection with each interferer. In other words, initially, the link cannot transmit at the same time as the interfered transmitter which provides the highest interference level to it. Then it will analyze from the second highest interfered transmitter to the lowest interfered transmitter. Iif the SINR of the link is still below the SINR threshold, then link l also cannot transmit at the same time as the second highest interfered transmitter. The modified interference level will keep being re-evaluated until the SINR of the link is below the SINR threshold (stage *3* to *6* in Figure 7-3), so that the current i_{th} highest interfered transmitter and the rest of transmitters can transmit simultaneously with link l by using the same channel.

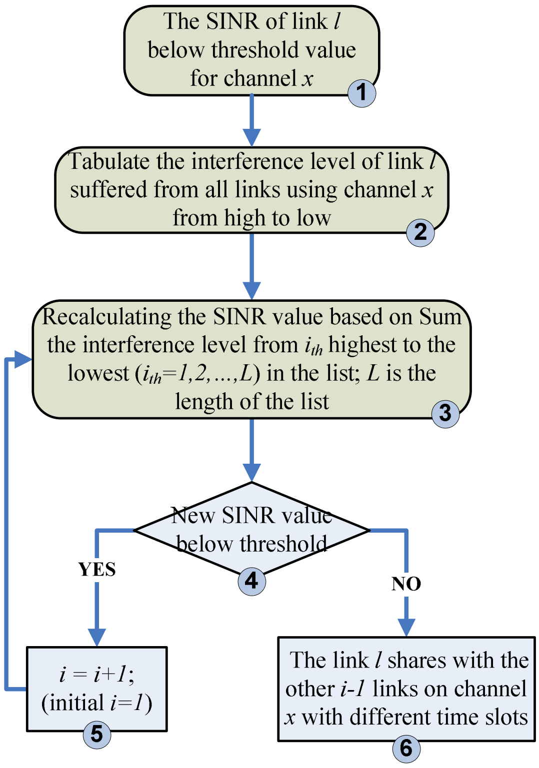


Figure 7-3 Flowchart of time sharing scheme

The following are the assumptions made to prevent packet collisions.

- Receiver nodes can distinguish the number of interfered transmitters as well as their individual interference level, so that each link has an interference list to indicate from highest interfered transmitter to the lowest one.

- We assume the time sharing scheme is symmetrical, which means if link A detects that it cannot transmit simultaneously with links B and C, then links B and C are also aware that they cannot transmit at the same time as link A regardless whether their SINR value at the receiver is above the SINR threshold.

- A perfect sharing scheme is applied here to make sure that each link occupies a different time slot with its interfered links.

Time division multiple access is used here to allow different links to access the full channel bandwidth at different times. A time unit (T) is subdivided into *M* notional time slots where T indicates the time taken at the current event. So the link can transmit at a high data rate within its assigned time slots. For example, in Figure 7-4, links A, B, C and D all use the same channel to fulfil their own transmissions. After the time sharing process in Figure 7-3, it appears that link A cannot transmit at the same time as links B and C, but can transmit at the same time as link D, thus we say that link A needs to be time shared with B and C. Therefore, only *M/3* time slots can be assigned to link A during time T. The higher number of links that are time shared with a link, the fewer time slots can be assigned to the link. More details of the time sharing scheme of Figure 7-4 can be found in Table 7-6, link A and C can be only assigned with *M/3* time slots each to fulfil its transmission on this channel; only *M/4* time slots can be allocated for each link B and C. Although the detail of how and when time slots are assigned to each transmission is beyond the scope of this thesis, one of example is illustrated in Figure 7-5 to help the reader to understand the concept of the time sharing scheme we applied. Notice that our time sharing scheme is not the most efficient scheme as there is *1/6* channel wasted due to the *M/6* time slots that are not assigned to any link as shown in Figure 7-5.

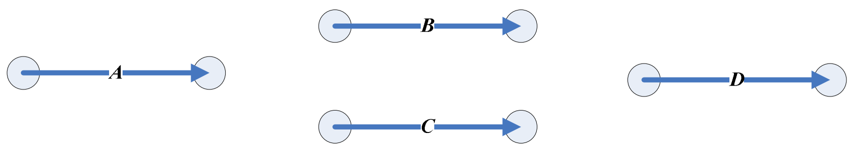


Figure 7-4 Example of links sharing different time

Links	A	B	C	D
A	N/A	N	N	Y
B	N	N/A	N	N
C	N	N	N/A	N
D	Y	N	N	N/A

Table 7-6 Table of the time sharing scheme; N/A indicates not available; N represents links cannot transmit at the same time; Y means links can transmit at the same time.

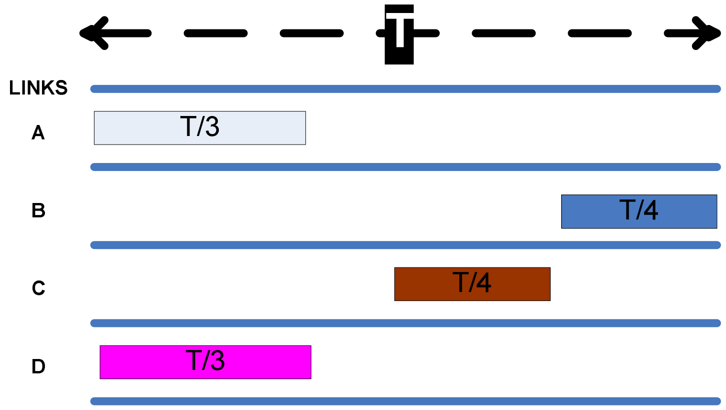


Figure 7-5 Example of how time slots are assigned to each link

Packet collisions will not take place in this scenario due to the application of the perfect time sharing scheme. In practice, real MAC schemes will generate overheads to achieve such behaviour. Therefore, retransmission only takes places where the transmitter detects that no channels can be available for its transmission due to the interference level it suffers. Hence, the transmitter of the link senses the status on all the channels until one of them becomes idle. Then, the link will start its transmission. Figure 7-6 illustrates the flowchart of the proposed MAC scheme we use. The proposed MAC scheme is similar to the 1-persistant CSMA scheme.

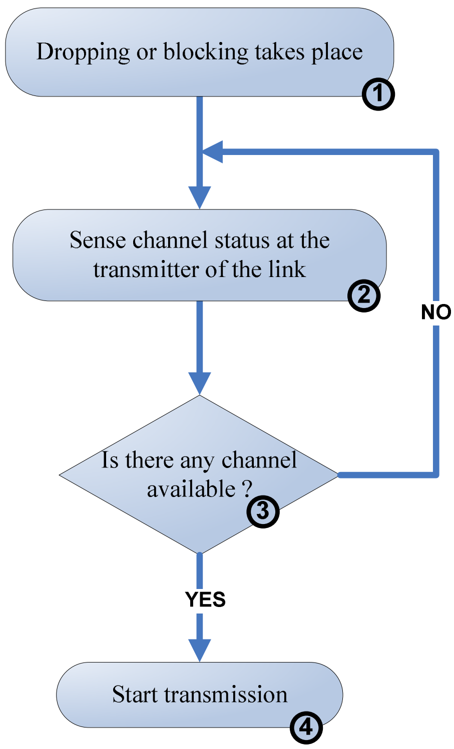


Figure 7-6 The flowchart of the MAC scheme

7.4 Cognitive Cross-layer Design

The channel assignment and routing should be jointly considered as both schemes will be invoked when there is a change in the network topology [84]. In this section, we will introduce the benefit of associating cognitive greedy-backhaul routing (CGB) with a reinforcement learning based channel assignment scheme (RLCAS) by comparing with other combinations of varying routing with varying channel assignment schemes such as shortest path by hops (SH) with RLCAS, shortest path by hops (SH) with sensing based channel assignment scheme (SCAS) and interference level based routing (ILR) with RLCAS.

7.4.1 CGB with RLCAS

Since the details of CGB routing have been introduced in the last chapter, we know that CGB prefers to select links that are heavily utilized, which means CGB invokes fewer nodes to relay network traffic. Thus, energy consumption can be minimized by switching nodes into sleep mode except for active nodes. The reinforcement learning based channel assignment scheme (RLCAS) with CGB (CGB_{RL}) can form an efficient cross-layer design due to the route selection feature of CGB, which provides a relatively slowly changing environment for RLCAS as it prefers links that have been currently utilized to new ones. With a suitable channel assignment scheme, channels can be allocated efficiently around the network without or with limited interference, so that additional capacity is assigned to crowded links where needed. In addition, the link weight of CGB depends on the channel utilization level which requires cross-layer information from the channel assignment protocol. Therefore, the cross-layer design of combining CGB with RLCAS not only can reduce the complexity for the channel assignment scheme but also improve the capacity of wireless ad hoc networks as well as reducing network energy consumption.

7.4.2 SH with RLCAS and SCAS

SH can also associate well with RLCAS (SH_{RL}) as it selects a fixed path from a specific source to a specific destination as long as the network topology remains the same. This feature of route selection provides a relatively stable environment for RLCAS. Although SH_{RL} can deliver similar performance on channel selection as CGB_{RL}, it does not take other network factors into consideration when establishing paths. Therefore CGB_{RL} can outperform SH_{RL} in network energy consumption as it prefers to relay traffic through those nodes that have already been activated.

Associating SH with SCAS ($SH_{Sensing}$) can show how the channel assignment scheme impacts on the network performance when the same routing is applied. The following section will show the result that a better channel assignment scheme can have a more significant impact on overall network performance than a better routing strategy.

7.4.3 ILR with RLCAS

In low traffic demand wireless networks where the radio spectrum is sufficient to fulfil traffic flows, it is encouraged to route around current existing traffic flows without potentially reducing the network capacity. Traditional ad hoc routing metrics, like shortest path, cannot take the interference level into account. Higher capacity links might remain unused and lower capacity links might end up being crowded. As a result, in wireless ad hoc networks, it is essential to relay more traffic through the higher capacity links so that network capacity can be improved.

In chapter 3, we presented a family of interference routing metrics whose link weight is calculated based on the number of disturbed nodes within the interference range which is defined as a fixed circle around the transmitting node. Here, the interference level is calculated in a more practical way as the ILR routing algorithm is based on the summation of the interference level that a node suffers on each channel. The received interference level from unexpected transmitters is determined by the path loss model and the transmit power which are illustrated in the previous sections. The link weight of ILR is determined by:

$$w_{ij} = \sum_{X=1}^{|P|} I_c, \forall i, j \in V; I_c \in \{I_1, I_2, I_3 \ldots .. I_{|P|}\} \tag{7.8}$$

Where I_c is the received power of node j by all transmitters using channel c. $|P|$ is the total number of channels in the network.

One of the disadvantages of ILR routing is the relaying burden it generates. ILR tries to route around congested nodes/links as they suffer significant interference. Therefore, there may not be sufficient channels in the network due to the extra relaying ILR generates. Another disadvantage of ILR routing is the dynamic feature of route establishment as the link weight depends on the current interference level which is related to the traffic pattern. This results in a difficult learning environment for RLCAS as the environment changes faster than the process of learning.

7.5 Capacity Analysis

In this section, we will use mathematical analysis to illustrate the upper bound and lower bound capacity a link can obtain in our network model.

L denotes the expected path length that a packet is traversed from a source node to a destination node. Then, the minimum hop number of the path is

$$H = \frac{L}{r} \tag{7.9}$$

where r is the transmission range of each node. Therefore, the minimum number of activated links at certain traffic load λ is

$$L_N = \frac{L}{r}\lambda \tag{7.10}$$

As the traffic load in this thesis represents the number of path flows, W represents a channel's maximum capacity. In the worst case scenario all of these links are assigned to an identical channel and are close to each other so that they have to share the capacity due to their interference. The capacity of each link can only obtain a portion of the channel capacity with respect to the number of activated links.

Considering the shortest path by hops routing metric (SH) here, then the expected number of links is $\frac{L}{r}\lambda$ as it can generate the minimum hop number amongst all routing metrics. This is the lower bound capacity for a link (using SH).

$$C_L = \frac{W}{L_N} \tag{7.11}$$

In the best case scenario where all links are far away from each other, channel capacity can be utilized by each of them due to channel spatial reuse. Then the capacity of each link can obtain the maximum channel capacity. This represents the upper bound capacity for a link.

$$C_U = W \tag{7.12}$$

We can define the capacity of a link as

$$C_l = \frac{W}{L_N}\delta, \quad 1 \le \delta \le L_N \tag{7.13}$$

where δ represents the parameter of channel spatial reuse which is affected by node's transmission range, path loss model, channel assignment scheme, SINR threshold etc. It is between *1* (lower bound) and L_N ($L\lambda/r$ - upper bound). If δ approaches the expected number of activated links, the scheme is considered to be better as a lower number of links share a channel temporally due to more efficient channel spatial reuse. In this case, links which have been assigned with the same channel are far away so that the transmissions can be carried simultaneously. In contrast, if δ approaches to 1, the number of links which are sharing the same channel increases. To avoid channel collisions, those links have to share the channel temporally so that results in lower obtainable capacity for each of them due to the high competition.

Since the parameters of r, λ, W are fixed and known in our network model, in order to determine a link's capacity we have to find out the expected path length which is influenced by the routing metric design. It is quite difficult to deduce the path length of certain routing metric designs as the path length is not only related to the network area but is also related to the weight function we defined for the routing metric. Therefore, we will only provide the expected path length of using shortest path by hops (minimum hop count) as the path length is only a function of network area instead of routing metric due to its fixed weight function.

In [30], Li shows the probability density function (*pdf*) giving the probability of a node communicating with another node at distance x as

$$p_x = \frac{x}{\int_0^{\sqrt{A}} t \ dt} = \frac{2x}{A} \tag{7.14}$$

where A indicates the network area and the integral is from 0 to $\sqrt{A}$ as $\sqrt{A}$ is the maximum distance a path can traverse using shortest path by hops for a square network when the source node or the destination node is selected at the centre of the network.

Therefore, the expected path length for a random traffic pattern is

$$L = \int_0^{\sqrt{A}} xp(x) \ dx = \frac{2\sqrt{A}}{3} \tag{7.15}$$

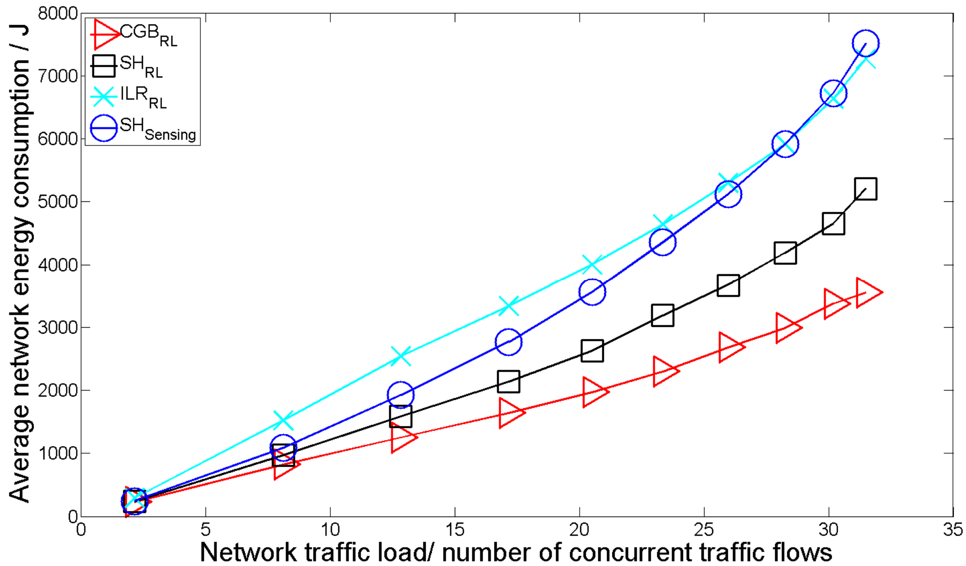
This expected path length is only valid for the shortest path routing metric. Other routing metrics should have larger path length as they generate more relaying hops and traverse longer distances. The shortest path by hops has the lowest expected path length among all routing metric designs, which proves that routing metric design should take path length into account in order to improve channel capacity. From equations (7.10), (7.13) and (7.15), we can deduce the link capacity of the shortest path by hops routing metric if we can determine maximum channel capacity, transmission range, traffic load, channel spatial reuse factor (δ) and network size:

$$C_{l,S} = \frac{3rW}{2\lambda\sqrt{A}}\delta, \quad 1 \le \delta \le L_N \tag{7.16}$$

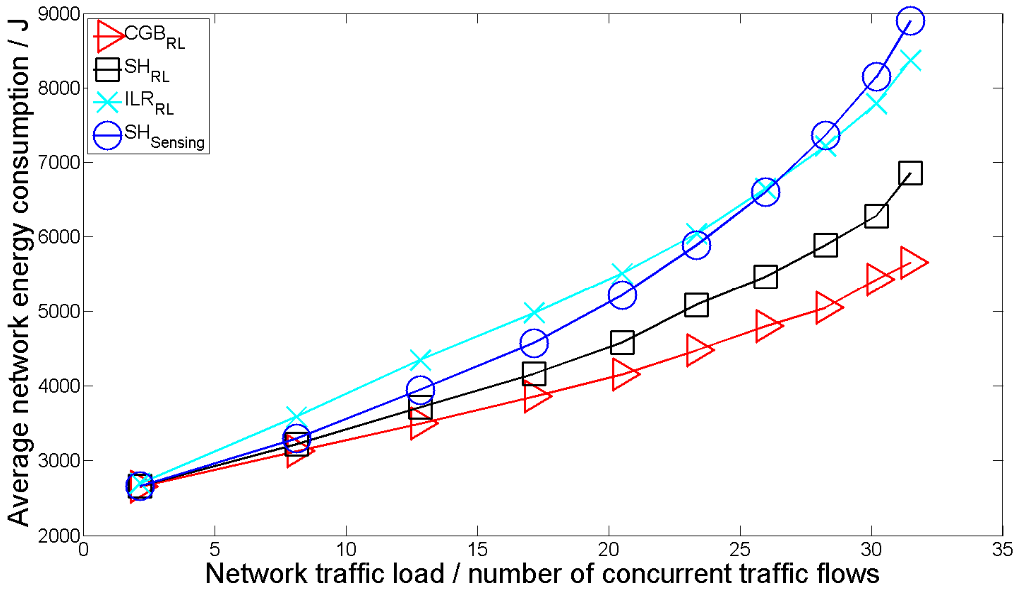
7.6 Energy Performance

In this section, we compare the network performance by using the proposed cross-layer design, cognitive-greedy backhaul routing with reinforcement learning based channel assignment scheme (CGB_{RL}), the shortest path by hops (SH) with sensing based channel assignment scheme ($SH_{Sensing}$), the shortest path by hops with RL based channel assignment scheme (SH_{RL}) and the interference level routing with reinforcement learning based channel assignment scheme (ILR_{RL}).

Figure 7-7 shows the average network energy consumption in a best case scenario (a) and a worst case scenario (b) using different schemes. Both scenarios illustrate that CGB_{RL} has significantly reduced energy consumption compared with the others. Each point along each result is collected based on the total network energy cost from the first event to the last event among *5* repeated simulations at a certain network traffic load. Initially, CGB relays traffic from source to destination based on minimum hop count as SH and then forces other traffic to a flow through the popular links due to their important geographical locations to build trunked backhaul links. Therefore CGB uses the minimum number of activated nodes (transmitting or receiving) to fulfil its transmission. Comparing CGB_{RL} with SH_{RL} and ILR_{RL}, the results of delay are similar as they are using the same channel assignment scheme, whereas CGB improves the energy consumption up to *35%* and *51%* respectively in the best case scenario, due to the unnecessary relaying/nodes that is generated/invoked by SH and ILR. Although traffic flows are concentrated in the backhaul links, the RL based channel assignment scheme can provide additional capacity by allocating channels efficiently without causing hidden terminal problems, so that activated links can have the maximum channel capacity for transmission as time sharing contention occurs less frequently. As aforementioned in the energy consumption model section, the total network energy consumption (E_{total}) is also a time constraint as it relates not only to the number of nodes in different power modes but also to each event time. Hence, a poor channel assignment scheme results in a longer delay, which indicates a longer activation time for activation nodes. For example, the sensing based channel assignment scheme ($SP_{Sensing}$) cannot solve the hidden terminal problem; thereby delay is increased due to the inefficient channel allocation methodology as shown in Figure 7-8. SH_{RL} improves the total network energy consumption up to about *31%* and *23%* compared with $SP_{Sensing}$ in the best and worst case scenarios respectively, even when the same routing strategy is applied. In addition, CGB_{RL} illustrates a greater advantage on energy saving by increasing the network traffic load. This is due to CGB which relays traffic through nodes that have already been activated, whereas SH requires many more nodes to relay its traffic thereby increasing the overall network traffic load.



(a)



(b)

Figure 7-7 Average network energy consumption with different schemes against network traffic load in the (a) best case scenario, (b) worst case scenario

7.7 Delay and Throughput Performance

Figure 7-8 shows the average delay against network traffic load among different schemes. Each point along each result is collected based on the mean delay among all activated end-to-end traffic flows from the beginning of the events to the last event for a certain network traffic load. Intuitively, SH_{RL} should outperform in terms of delay compared with the other schemes as SH routing generates the lowest relaying burden in the network. Nevertheless, CGB_{RL} and ILR_{RL} have similar performance to the SH_{RL}. This is because they all use the same channel assignment scheme, reinforcement learning based channel assignment scheme (RLCAS). With a relatively slowly changing environment, e.g. end-to-end traffic flows remaining in the network for sufficient events, the learning engine of RLCAS can obtain enough environment information in order to assign channels in a more efficient way. Despite the routing schemes we applied, a good RL based channel assignment scheme in a slow changing network environment, it should aim to allocate suitable channels for links with regard to their locations. In other words, channel assignment should adapt well with environment changes such as traffic pattern, nodes movement etc. As shown in Figure 7-8, CGB_{RL},

SP_{RL} and ILR_{RL} reduce the average traffic delay significantly, compared with $SP_{Sensing}$ by up to about *47%*, *37%* and *31%* respectively. The sensing based channel assignment scheme cannot detect hidden terminals, and therefore channel interference occurs and channel capacity is shared by those links time sharing with each other as shown in Figure 7-3. Finally, delay is increased as less channel capacity is allocated for those transmissions due to the contention on the same channel.

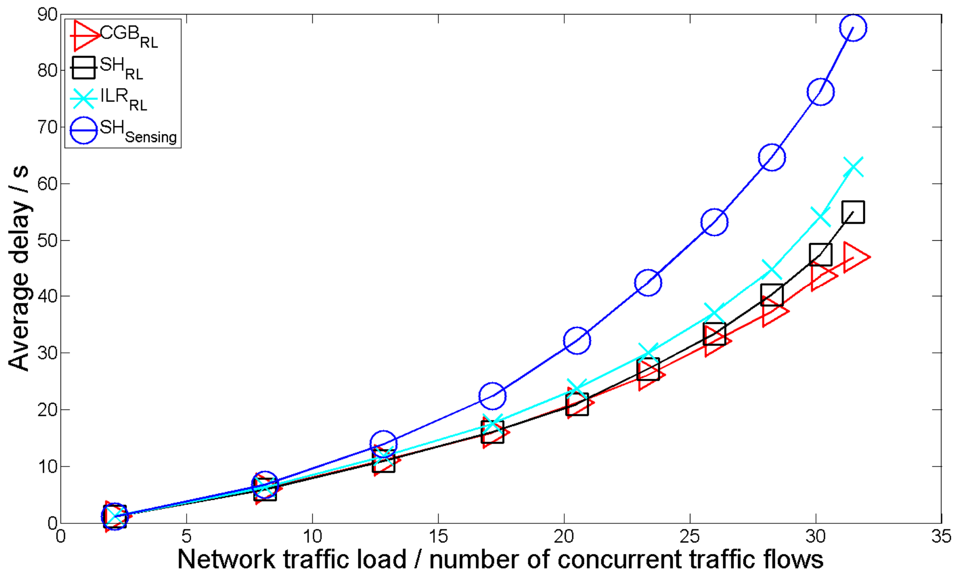


Figure 7-8 Average delays with different schemes against network traffic load

Figure 7-9 further proves the result shown in Figure 7-8 as the time sharing probability of using a sensing based channel assignment scheme is much greater than the reinforcement learning based channel assignment scheme with different routings. The time sharing probability indicates how often the time sharing scheme occurs using each scheme. Since the sensing based channel assignment scheme cannot detect the interference level at the receiver end of the link, it suffers from the hidden terminal problem when assigning channels. Although the reinforcement learning-based channel assignment scheme is not a perfect solution for solving the hidden terminal problem, with the learning knowledge it gains from the environment which includes the traffic pattern, neighbour channel utilization etc., it is able to punish the bad channels and reward the good ones. Therefore the future decision on the channel selection will be influenced by the learning knowledge gained from past, so RLCAS is a better solution for solving hidden terminal problem than SCAS.

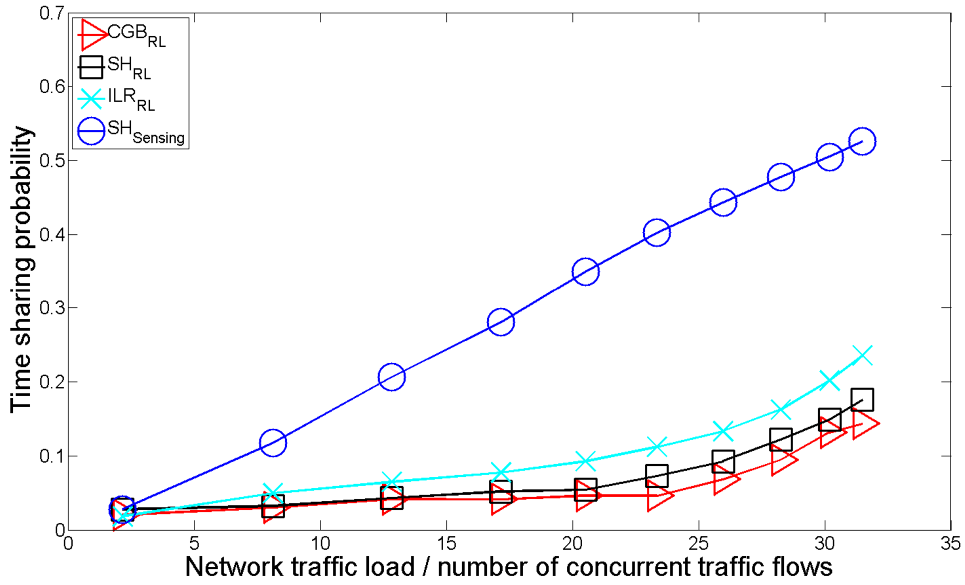


Figure 7-9 Average dropping probability with different schemes against network traffic load

Figure 7-10 illustrates the average end-to-end throughput performance for the different schemes. The lower bound and upper bound capacity (from section 7.5) are also drawn in Figure 7-10. As can be seen from the figure, the end-to-end bottleneck throughput of using reinforcement learning based channel assignment schemes lie close to the upper bound. This is due to the fact that reinforcement learning based channel assignment schemes not only can mitigate the hidden node problem but can also assign suitable channels to each link due to their locations and network traffic in order to maximise the channel spatial reuse through learning. In contrast, the sensing based channel assignment scheme indicates worse performance on throughput, compared with those routing metrics that are using a RL based channel assignment scheme. This is due to its poorer ability to deal with channel spatial reuse by comparison with RL based channel assignment schemes.

The throughput of ILR_{RL} is slightly better than other schemes at the lowest traffic load. The reason was explained in Chapter 3, as ILR can relay traffic through the edge of the network to avoid congested areas without causing further bottlenecks as there are sufficient channels available for the extra relaying. In general, ILR has the lowest throughput among those routing metrics by using the same channel assignment scheme (RLCAS) as expected. The weight of each link of ILR is calculated based on the summation of power received from all activating transmitters. Due to the characteristic of ILR, extra hops are needed which consumes more network capacity. In addition, ILR encourages the upcoming traffic flow to shift to a less crowded area due to the concurrent interference levels. This dynamic routing selection results in an inefficient learning process for RLCAS as the link usage of using ILR is much smaller than CGB (evidence can be found in next section). Intuitively, ILR^k and ILR_{th} (illustrated in Chapter 4) consume more network capacity compared with ILR under high traffic load conditions.

An interesting point is that using different channel assignment schemes can improve the network performance more significantly than using different routing strategies. As shown in Figure 7-10, SH only improves the network average throughput up to about *14%* by comparison with ILR when RLCAS is applied to both routing schemes, whereas RLCAS shows a throughput improvement of up to *61%* by comparison with SCAS when the same SH routing is used. As expected from (7.13), in Figure 7-10, RLCAS illustrates a better channel spatial reuse (better δ) than SCAS by using the shortest path by hops routing metric design. In a poor channel assignment scheme, more links compete for the same channel which results in lower obtainable capacity for each link. Comparing the two schemes RLCAS with ILR and RLCAS with SH, RLCAS with SH shows much better results in end-to-end throughput as the expected path length of using ILR is much longer than using SH. This implies that a good routing metric design should take path length into account in order to reduce relaying burden impact. In equation (7.13), although shortest path by hops has the lowest path length and both schemes of CGB with RLCAS and SH with RLCAS use a reinforcement learning based channel assignment scheme, CGB with RLCAS provides a better end-to-end throughput in Figure 7-10. This is due to a better channel spatial reuse (better δ) as reinforcement learning based channel assignment scheme can combine better with a CGB routing metric than shortest path by hops routing metric (more details are given in Figure 7-11and Figure 7-12).

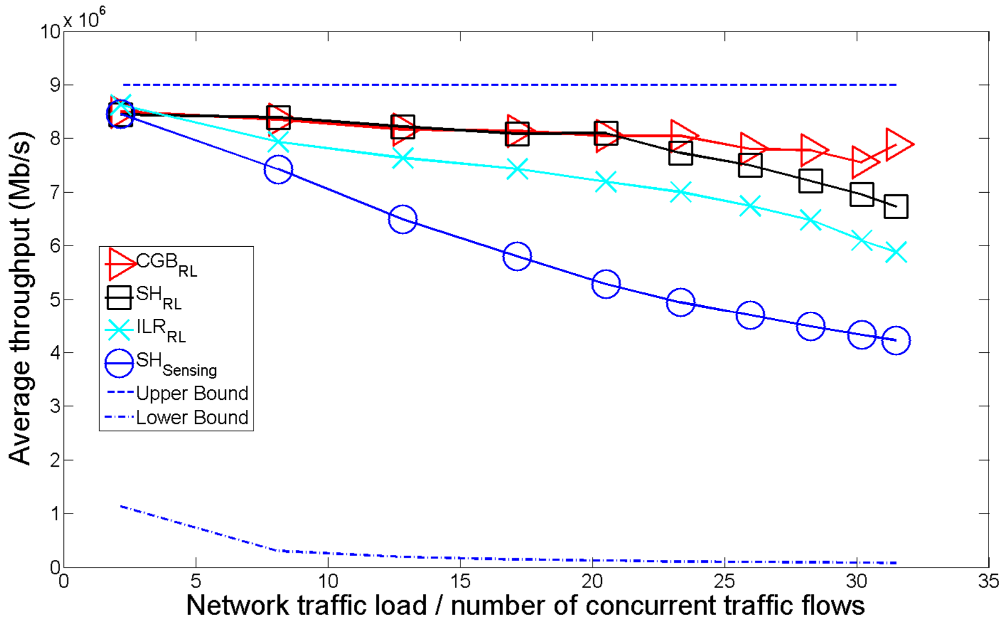


Figure 7-10 Average end-to-end throughput with different schemes against network traffic load

7.8 Learning Performance

The learning process of channel assignment can not only adapt with environment changes but can also affect the environment. Each decision of channel selection on a link affects the channel learning process of the other links. For instance, a bad learning process can reduce channel capacities due to co-channel interference and results in a longer occupation time on those channels; consequently, they will affect channel selections and learning process for other upcoming links. On the other hand, if a good channel decision is made, the traffic flow can fulfil the transmission task in a more efficient way and results in a shorter lifetime. Thus, more channels can be available for upcoming transmissions. A better reward can be achieved during a longer process if learning adapts well with the environment.

Figure 7-11 shows the Cumulative Distribution Function (CDF) performance on the utilization of links (link usage) by applying different routing metrics at an average traffic load of *31.5* end-to-end traffic flows. The x-axis (link usage) is plotted on a logarithmic scale. The utilization level of a link (link usage) is the number of times that the link has been activated. In CGB link usage, about *8%* and *5%* of total links exceed the maximum link usage of ILR (max utilization level = *43*) and SH (max utilization level = *70*) respectively and the maximum link usage among CGB links is about *248* which is around *6* times and *4* times than the maximum link usage of ILR and SH respectively. As expected, CGB has the ability to attract traffic flows through certain backhaul links due to their geographical location and SH has regular link usage levels among links due to the stable topology and the lack of ability to find alternative links for traffic relaying. ILR obtains on average low levels of link utilization as it disperses its transmission tasks to less interfered links. Those high utilization levels of links reflect the exploration ability to detect good channels as well as bad channels around them. In other words, the learning progress of each link is proportional to its link usage which is related to the routing metric we applied and the traffic pattern.

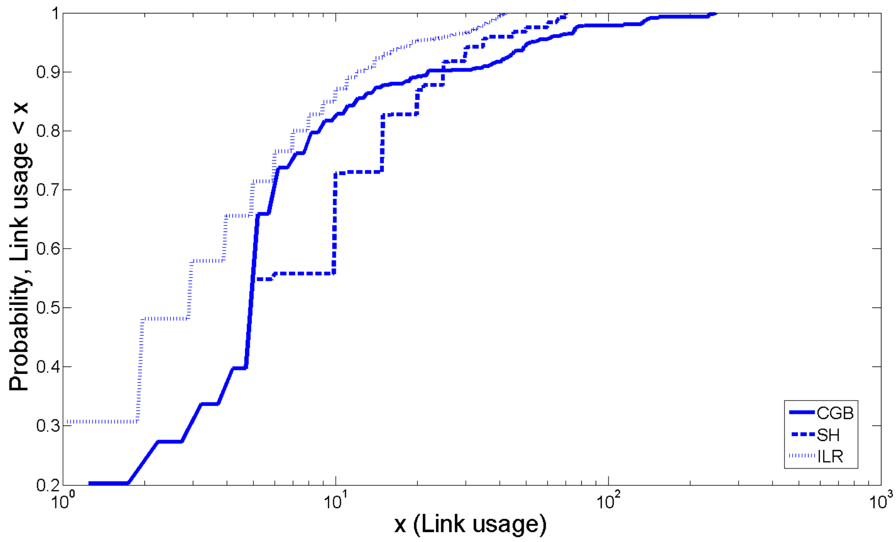


Figure 7-11 CDF of link usage at a traffic load of *31.5* traffic flows

A higher link usage indicates a better opportunity for a link to explore and exploit its most suitable channels as well as bad channels that are occupied in the vicinity with respect to the environment. CGB has more opportunities for links to find suitable channels as there are *5%* and *9%* of total links that have channel weight values which exceed *72* (highest weight value by using SH) and *40* (highest weight value by using ILR) by comparison with SH and ILR respectively. This result can be seen in Figure 7-12 which is the CDF of channel weight value at the same traffic load as in Figure 7-11. The graph only shows the extreme conditions of high and low weight values as the middle range of channel weight values has similar performance among these routing metrics. In the high weight value section (graph a), a certain channel weight is rewarded with as high as *1090*, *963* and *951* for CGB, SH, and ILR links respectively. This is due to the higher usage of those links that gain more opportunity to use and reward its best channels than those links with a low utilization level. On the other hand, in the low weight value section (graph b), although a few channel weights of CGB received punishment as low as *-330* compared to the minimum channel weight value of SH (*-42*) and ILR (*-29*), CGB still outperforms the other routing metrics in terms of time sharing probability, delay and throughput performance as shown in Figure 7-8, Figure 7-9 and Figure 7-10. The reasons are as follows. There are excessive activated links that require bandwidth for their transmissions as the performance is measured under an extremely high traffic load condition (*31.5* concurrent traffic flows), as well as the routing behaviour of CGB which accumulates those transmissions through backhaul links. Therefore, some bad channels are punished due to the excessive interference in the vicinity that is detected by the sensing scheme so that the link will avoid using those bad channels in future events. In other words, the large punishment value of links on certain channels does not indicate an inefficient learning progress; in contrast, it explores those channels that are preferred by its neighbour links in order to avoid channel collisions when it selects its own channels for transmissions. Conclusively, the learning progress of a link on channel assignment is proportional to the link's utilization level as a higher utilization level indicates more opportunities for the link to find the good channels and bad channels in its local environment.

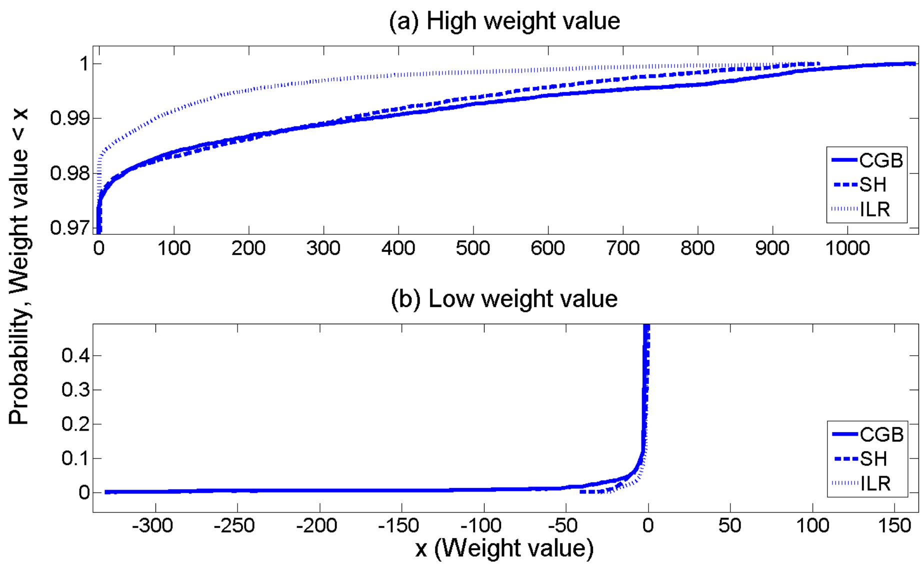


Figure 7-12 CDF of channel weight value at a traffic load of *31.5* traffic flows; graph (a) shows the extreme weight values at large reward section; graph (b) shows the extreme weight values at large punishment section

7.9 Conclusion

This chapter has shown the impact of cross-layer design in a more practical network environment by including a path loss model, a better interference model and traffic models as well as an energy model. It also studied each cross-layer scheme by associating different combinations of routing with each channel assignment scheme. A novel cross-layer design that combines the cognitive greedy-backhaul routing with the reinforcement learning based channel assignment scheme shows that RLCAS can be incorporated reasonably into CGB by assigning extra capacity to the backhaul links, and CGB uses a limited number of nodes to relay traffic flows. Our results show that the proposed cross-layer design of CGB with a RL based channel assignment scheme reduces the energy consumption without compromising throughput and delay. In addition, the learning progress of links on channel selections is examined with respect to the link usage. The results show that the CGB has the best ability to explore the good channels as well as the bad channels due to the routing behaviour of attracting transmissions through backhaul links which result in high link utilization levels.

Chapter 8

8 Exploiting a RL Channel Assignment Scheme

Contents

8.1 Introduction

From the previous chapter, we have seen that the cross-layer design of combining the reinforcement learning based channel assignment scheme (RLCAS) with cognitive greedy-backhaul (CGB) routing is a key technique to reduce network energy consumption while still maintaining other network performance in terms of end-to-end bottleneck throughout and delay. We also proved that applying a better channel assignment scheme can show a greater advantage than applying a better routing scheme. Therefore, in this chapter, we will further study the impact of applying different channel assignment schemes with CGB routing. Moreover, we will analyse the learning progress of RLCAS, and elaborate how the channel assignment benefits from the learning engine.

Maintaining network capacity is a big challenge for wireless ad hoc networks due to their multi-hop feature. Although relaying can help convey data on a multi-hop basis, the relayed traffic also need channel capacity. In wireless networks, the available frequency spectrum is precious and limited, and therefore channel spatial reuse is vital to increase network capacity. Hence, a proper channel assignment scheme is required for wireless ad hoc networks to allocate channels in a distributed manner for the large number of relaying links in order to reduce the blocking and dropping probability, as well as maximizing network QoS [85]. Traditional cellular channel assignment schemes are not suitable for wireless ad hoc networks. Fixed channel assignment (FCA) cannot be applied to wireless ad hoc networks as there is no central base station to allocate fixed channels to certain locations. In addition, FCA cannot adapt with environment changes such as changing of traffic conditions and user movement. Although dynamic channel assignment (DCA) can solve the problems from which FCA suffers, it has been proven that DCA does not perform well under heavy traffic load conditions [86]. In [84], Gong introduces a cross-layer design by combining the OLSR routing protocol with a channel assignment scheme to reduce channel collisions in wireless ad hoc networks. Gong's idea is to use the routing control messages of OLSR to exchange channel information up to *k*-hops. Therefore, it requires a significant control overhead up to *k*-hops to be able to reduce channel collisions caused by the hidden node problem.

Due to the decentralized nature of wireless ad hoc networks, we need a channel assignment scheme where transmitters can decide which channels are suitable for use in an autonomous process. Some research has proposed that users/nodes could find suitable channels in a distributed way by applying machine learning into the channel assignment scheme [76, 80, 87]. Although there are some research works using machine learning based channel assignment schemes, most of them focus on a single hop basis instead of a multi-hop basis. Therefore, the purpose of this chapter is to examine the learning process of using reinforcement learning based channel assignment schemes in a multi-hop approach associated with routing metric design.

The contents of this chapter are structured as follows. Firstly, we illustrate the network scenario. Next, we discuss the varying channel assignment scheme with CGB routing. This is followed by performance comparison results. We compare the results especially on the learning process of reinforcement learning based channel assignment schemes with and without sensing. Finally, conclusions will be given.

8.2 Network Scenario

The network parameters such as network size, node number, number of available channels, traffic model and path loss model have been provided in the previous chapter. Figure 8-1 shows the network layout. There are 100 nodes in total; top number indicates the node index; bottom number indicates the number of hops away from the destination node (node index 100 – indicated by a black triangle).

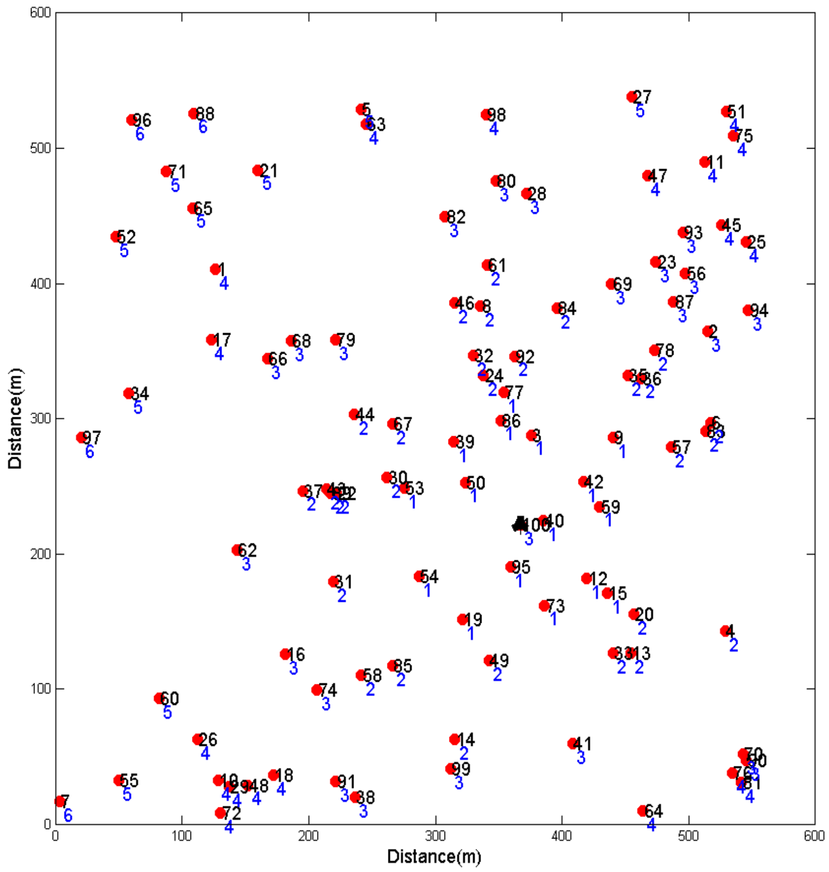


Figure 8-1 Network layout

8.3 RL Channel Assignment Scheme without Sensing

From Chapter 7, we have seen that a reinforcement learning based channel assignment scheme (plus sensing) when combined with a shortest path (SH) routing algorithm can deliver superior network performance, compared with a sensing based channel assignment scheme (SCAS) with SH. With the reinforcement learning based channel assignment scheme plus sensing, nodes can be aware of their neighbours' environment, and therefore eliminate the probability of channel collision in their vicinity. Although channel collisions can be limited by the sensing ability of each transmitter, channel collisions may still occur at the receivers due to the hidden node problem that was mentioned in Chapter 7. However, the sensing technique cannot solve the hidden node problem; it increases the control overhead and energy consumption, and it introduces the exposed node problem [88]. The exposed node problem occurs when a node is prevented from initiating packet transmission to other nodes due to the adjacent transmitter(s). Consider an example of 4 nodes (A, B, C and D) as shown in Figure 8-2 where two receivers A and D are out range of each other, but the two transmitters B and C are in range of each other. Theoretically, transmissions could happen simultaneously by using same channel as the destinations (A and D) are out of range of each other. In contrast, as node B starts to send its signal to A, node C is prevented from transmitting to D as it wrongly thinks a collision will happen due to carrier sense. This problem could limit the efficiency of channel spatial reuse. Therefore, we test the reinforcement learning without a sensing based channel assignment scheme (RL-NS-CAS) to study the learning impact on the channel assignment without sensing. Figure 8-3 illustrates the flowchart of RL-NS-CAS. Compared with the reinforcement learning based channel assignment scheme with sensing (RLCAS), RL-NS-CAS selects the highest weight channel and uses it straight away without sensing the channel status.

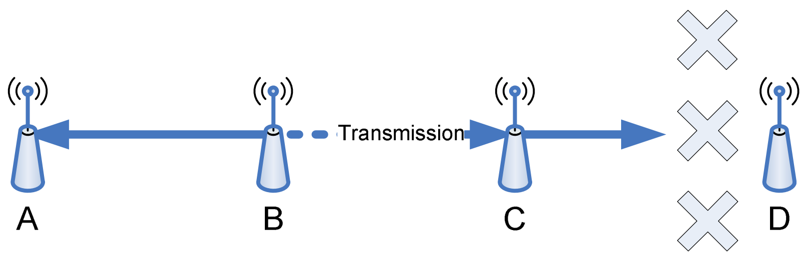


Figure 8-2 Exposed node problem

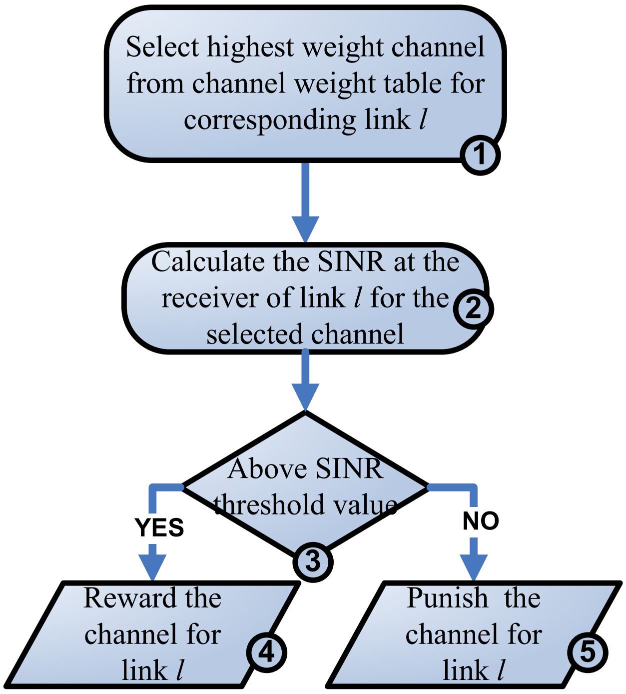


Figure 8-3 Flowchart of RL without sensing based channel assignment scheme

8.4 Performance

In the last chapter, we compared the network performance by applying RLCAS with different routing strategies, and the results showed that cognitive greedy-backhaul routing (CGB) with RLCAS outperforms the others. In this section, we will analyse the network performance by using CGB with different channel assignment schemes. Firstly, we provide the network performance including the delay, throughput and time sharing probability by associating sensing, RLCAS and RL-NS-CAS with CGB. Secondly, the learning performance versus different network traffic loads is also given. Next, the learning performance of each link is tested with different distances to the source node. Finally we illustrate the learning performance based on link usage.

8.4.1 Network Performance

Figure 8-4 and Figure 8-5 illustrate the network performance of delay and throughput respectively by applying CGB with different channel assignment schemes including sensing based, reinforcement learning with sensing and without sensing based schemes. The CDF results are analysed from a large amount of data which was collected through Monte-Carlo simulations using between *1* and *40* traffic flows at various traffic loads. Both results show a great advantage by using a learning-based channel assignment scheme with CGB, compared with the sensing based channel assignment scheme with CGB. As can be seen in Figure 8-4, with RLCAS and RL-NS-CAS the delay is improved by up to about *26%* and *16%* respectively compared with SCAS (at delay value of *43* seconds). Moreover, throughput using SCAS is only above *8.6* Mbps *9%* of the time, compared with *52%* and *58%* when using RL-NS-CAS and RLCAS as shown in Figure 8-5. As a result, the learning based channel assignment schemes deliver a better network QoS in delay and throughput than a purely sensing-based channel assignment scheme, as links are able to find their preferred channels through learning about their environment, in order to avoid hidden node problems.

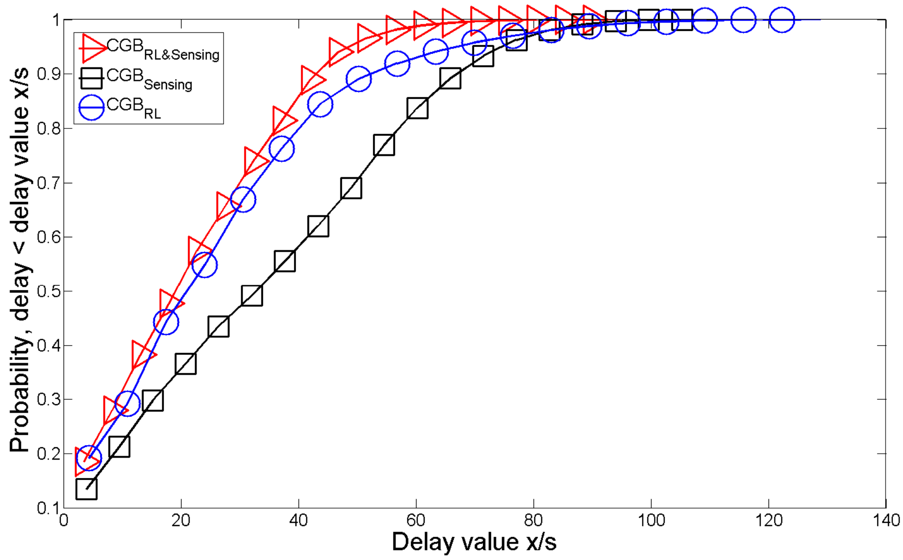


Figure 8-4 CDF of long-term end-to-end delay by using CGB with different channel assignment schemes

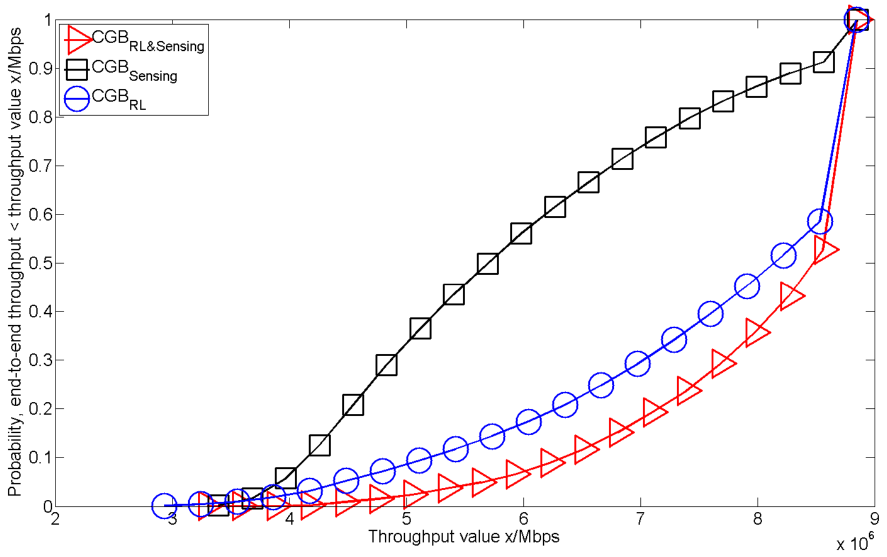


Figure 8-5 CDF of long-term end-to-end throughput by using CGB with different channel assignment schemes

Figure 8-6 shows the time sharing probability against network traffic load graph, using the time sharing scheme that was proposed in Chapter 7, where links are allocated to different time slots if they cannot use the same channel concurrently. This figure explains that the SCAS cannot avoid the occurrence of channel collisions and the probability of time sharing increases as network traffic load rises. Nevertheless, learning based channel assignment schemes have the ability to reduce the hidden node problem as they show a dramatic reduction of time sharing probabilities compared with SCAS. Figure 8-6 shows that using RL-NS-CAS and RLCAS, there are about *33%* and *35%* reductions on the time sharing probability than SCAS at a traffic load of *35* traffic flows. Furthermore, the graph illustrates learning based channel assignment schemes can maintain the time sharing probability at a similar level which is about *1%* to *5%*, even with the increasing of the network traffic load from *2* to *28* traffic flows. Therefore, this result indicates that for the network environment (includes network size, node number, transmission range, SINR threshold and etc.) used for this chapter, *100* channels are sufficient under a traffic load of *28* concurrent traffic flows and channel spatial reuse can be obtained through learning. On the other hand, the channel capacity reduces significantly when traffic load is above *28* flows as there is no additional channel capacity to fulfil those transmissions and relaying, and time sharing probability starts rising quickly with the increasing of the network traffic load. It is also to mentioning that RLCAS demonstrates a significant advantage on time sharing probability over RL-NS-CAS at very high traffic load. This is due to the different exploration abilities: RLCAS can adapt and react more efficiently with its sensing ability in a high traffic load network, whereas RL-NS-CAS adapts relatively slowly in a fast changing environment.

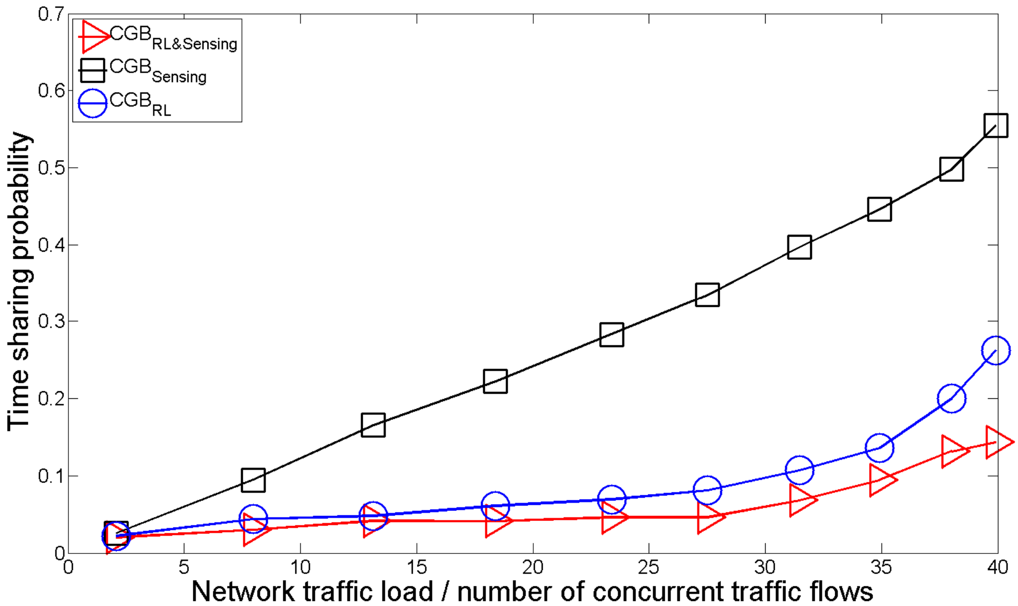


Figure 8-6 Average time sharing probability by using CGB with different channel assignment schemes against network traffic load

The aim of using a reinforcement learning based channel assignment scheme is to assign channels through a distributed approach where links/nodes can find their preferred channel/channels even with environment changes such as node movements and traffic patterns. The sensing can improve the efficiency of the exploration stage when the environment changes. Links can reward the good channels or punish the bad channels through learning in a relatively static environment to maximize the exploitation stage of reinforcement learning. In other words, the exploration stage of reinforcement learning-based channel assignment schemes function as DCA at the initial stage, so that suitable channels can be assigned to each activated link due to their positions and traffic patterns in order to avoid channel collisions. With the assistance of sensing, reinforcement learning can explore the environment more efficiently. After a long time operating the learning process, RLCAS performs more like FCA as links are allocated with fixed channel/channels with respect to their different locations in order to improve the channel spatial reuse.

8.4.2 Learning Performance Based on Traffic Loads

Figure 8-7 and Figure 8-8 illustrate how learning reacts with different network traffic loads when applying sensing or without sensing for a reinforcement learning based channel assignment scheme. The x-axis (the channel weight ranking) is plotted on a logarithmic scale. Results are collected from a channel weight table which is a $|m|$-by-$|n|$ matrix (C_{mn}) where $|m|$ indicates the total number of links and $|n|$ represents the number of channels available in the network. In the network scenario shown in Figure 8-1, there are a total of *938* links and *100* channels available in the network. M and N denote the set of links and the set of channels respectively. To obtain the values of the y-axis in Figure 8-8 and Figure 8-7, first the matrix C_{mn} is sorted at each row in a descending order.

$$\overrightarrow{C_{mn}} = sort(C_{mn}, 'descend'), \{n_1 \geq n_2 \geq ... \geq n_{|n|}; n_{|n|} \in N\} \tag{8.1}$$

Then we treat the columns of C as vectors, returning a row vector of the sums of each column. Therefore now we have a vector (W) with *100* elements which indicates the sums of the channel weight values from the highest rank weight channel to the lowest rank weight channel among all links.

$$W_i = \sum_{j=1}^{m} m_j, m_j \in M_i, M_i \subset C_{mn}, i = 1,2,...,|n| \tag{8.2}$$

Next, we can calculate the total channel weight value by sum of W_i.

$$W_{total} = \sum_{x=1}^{|n|} W_x, W_x \in W_i \tag{8.3}$$

Finally, the normalized channel weight value of each summation channel weight is calculated from the highest rank weight channel to the lowest rank weight channel.

$$W_{norm} = \frac{W_i}{W_{total}}; i = 1,2,...,|n| \tag{8.4}$$

These two graphs can illustrate how fast the learning rate is for each scheme under different network traffic loads. Figure 8-7 shows that the learning rate of the reinforcement learning based channel assignment scheme with sensing is almost identical to the scheme without sensing under a low network traffic load condition as the sum of the high rank weight channels (rank *1* to rank *10* perhaps) accumulate to a similar weight value through learning. This is due to the environment which changes relatively slowly under a low traffic load, so that the exploration ability does not have a significant impact on the learning process although RLCAS shows a better exploration ability than RL-NS-CAS due to the assistance of sensing. The channel weight values of the sensing based channel assignment scheme (SCAS) are collected for reference comparison to those learning schemes. As expected, the channel weight value of SCAS demonstrates almost a uniform distribution figure as the accumulated channel weights are based on instantaneous sensing rather than historical learning.

On the other hand, for a high traffic load condition where the network changes relatively quicker due to the traffic pattern, RLCAS achieves a better learning rate than RL-NS-CAS at high ranking channel weights between the highest and *10th* highest channel weights. This proves that RLCAS can adapt better and faster to a dynamic environment than RL-NS-CAS due to its better exploration ability thanks to the sensing.

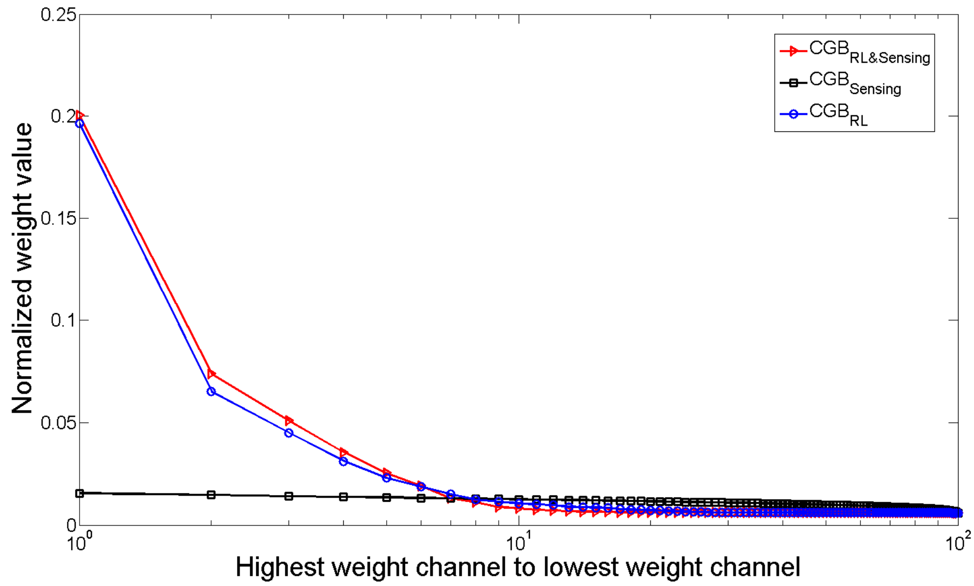


Figure 8-7 Normalized channel weight against channel weight ranking from the highest to the lowest at a traffic load of *13* traffic flows (low traffic load) with different channel assignment schemes

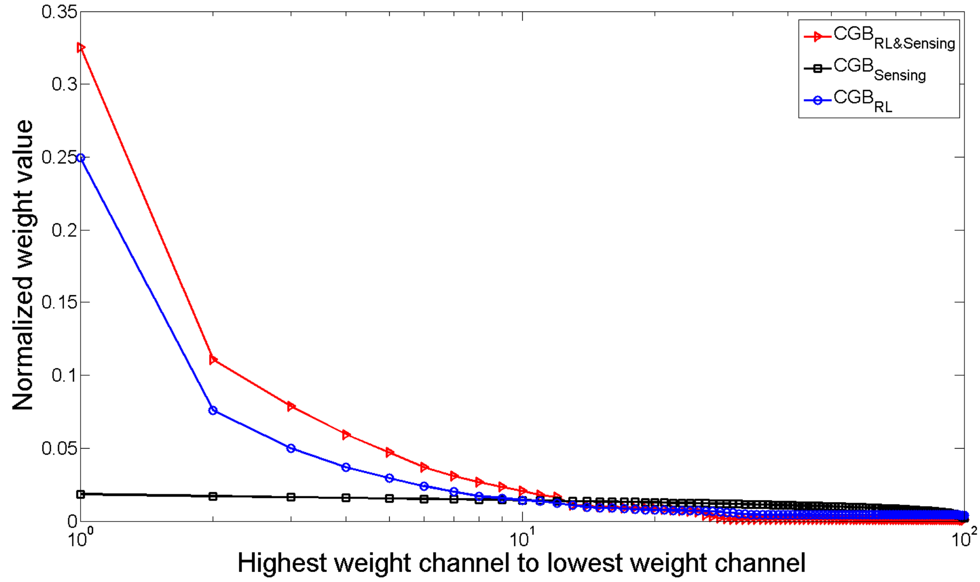


Figure 8-8 Normalized channel weight against channel weight ranking from the highest to the lowest at a traffic load of *37* traffic flows (high traffic load) with different channel assignment schemes

8.4.3 Learning Performance Based on Distance (hop)

In this section, we examine the learning impact on links with different geographical locations where the distance of a link with respect to the common destination is taken into account. Figure 8-9 shows the learning rate of links for the highest accumulated weight channel x hops away from the destination node at different events, by using CGB with RLCAS at network traffic load of *37* flows. The results of each mean of the highest channel weight among the different links are collected at event *100*, *300*, *600* and *990* (the end of the simulation).

From the network layout shown in Figure 8-1, the furthest nodes from the destination node are *6* hops away ($|h|$ is *6*). The node distance table and the link distance table are shown in Table 8-1 and Table 8-2 respectively.

	1 hop	*2* hops	*3* hops	*4* hop	*5* hops	*6* hops
Number of nodes	*16*	*29*	*22*	*19*	*9*	*4*

Table 8-1 Node distance table

	1 hop	*2* hops	*3* hops	*4* hop	*5* hops	*6* hops
Number of links	*16*	*80*	*71*	*53*	*22*	*8*

Table 8-2 Link distance table

Therefore, for each hop, there is a $|m|$-by-$|n|$ matrix (L_{mn}) where $|m|$ indicates the number of links that are x hops away as shown in Table 8-2 and $|n|$ indicates the available channel number (*100*). We denote the element of matrix L_{mn} as $l_{i,j}$ where $i = 1,....,|m|$ and $j = 1,....,|n|$. Then to obtain the values at y-axis in Figure 8-9, we take out the maximum weight value from each row (link), therefore W is a vector that contains $\{W_1, W_2,...., W_i\}$.

$$W_i = \max(l_{i,1}, l_{i,2}, ...l_{i,|n|}), i = 1,2,...., |m| \qquad \textbf{(8.5)}$$

The result is collected by taking the mean of each vector W through different hop numbers from *1* to *6*.

$$\overline{W_h} = mean\ (W_1, W_2, \ldots\ldots, W_i),\ h = 1,2,\ldots., |\ h\ | \tag{8.6}$$

This figure illustrates that links that are far away or close to the destination learn faster than the links in the middle range. For the links that are close to the sink, they have been utilized more often than the others as they not only transmit their originated traffic but also need to relay traffic for others. Consequently, they obtain greater opportunities to find their best channels. For the links that are on the edge of the network, although they achieve the lowest utilization level, they suffer minimum interference from other activated links. Therefore their learning is quite efficient due to the relatively slower changes on the edge of the network. In contrast, the links in the middle range suffer high interference, and experience a more unstable environment, so that it takes a longer time to step into the exploitation stage of the reinforcement learning. It is worth noticing that even the learning rate of links that are in the middle range is not as fast as the far side and near side links, and the weight of the highest ranking channel still keeps increasing with the time. In other words, they can still achieve good learning as the best channel keeps being rewarded in general. For example, in Figure 8-9, links that are *3* hops away from the sink node accumulate the highest channel weight value from about *15* at event *100* to *110* at the end of the simulation.

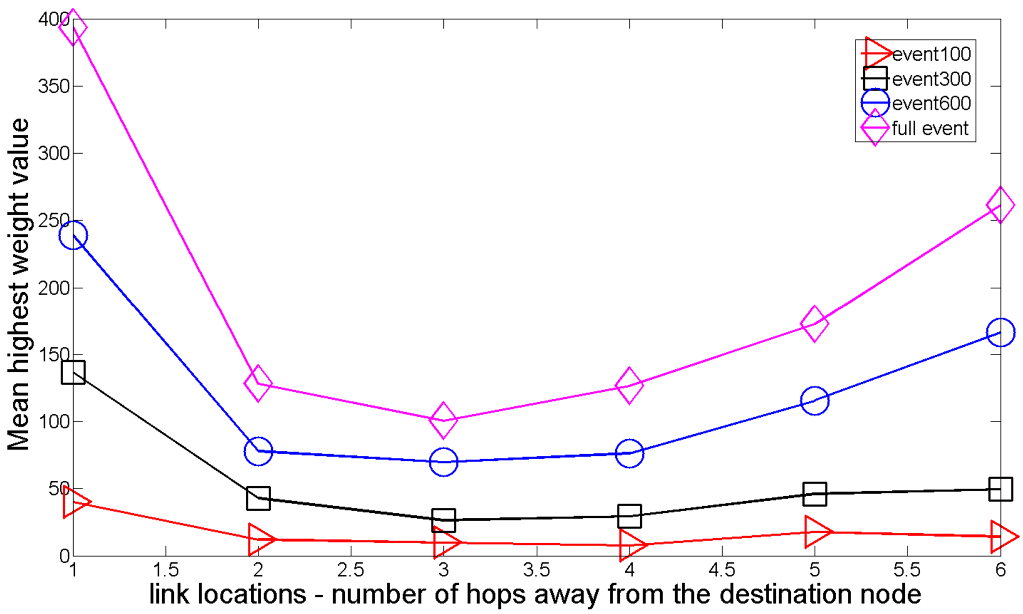


Figure 8-9 Summation of highest channel weight comparison with different link location with respect to the destination node at varying events under traffic load of 37 traffic flows

8.4.4 Learning Performance Based on Link Usage

In the last section, we have seen the learning impact for links with different geographical locations and this illustrated that links that are close to the destination can achieve a higher channel weight value than those links that are bit further from the destination due to their relatively high link usage. Therefore, in this section, we will examine the learning process for links with varying utilization level which is mainly related to the application of the routing metric, the links' locations and the network traffic pattern. The results are collected under a heavy traffic load of *37* traffic flows.

Figure 8-10 and Figure 8-11 illustrate that the learning process on finding good channels and bad channels is dependent on link usage. Notice that the link usage (x-axis) of Figure 8-10 is plotted on a logarithmic scale. The higher the link usage, the better the opportunity the link has had to explore and exploit its best suitable channels as well as the poor channels with respect to the environment. As can be seen in the link usage graph (Figure 8-10), at event *100*, about *10%* of the total activated links that have been used about *11* times with a maximum link usage of *33*. Due to the excessive traffic loads and the behaviour of the CGB routing metric which accumulates traffic through certain backhaul links, here *10%* of the total activated links have been used about *20* times and *28* times up to event *300* and *600* respectively, with some link usages that can reach a maximum value as high as *75* for event *300* and *176* for event *600*.

In Figure 8-11, the channel weight values at each event are collected from the channel weight table (C_{mn}) of the links that have been activated up to the current event rather than the whole link set as there are an excessive number of potential links in the network (*938* links in this topology) but only a fraction of these links (e.g. only *142* links are used out of *938* available links) have been utilized due to their locations and the applied routing metric (SH and ILR would use more links as discussed in the previous chapter). There are still large number of channels that cannot be used for a certain link as in the channel weight table, one link has *100* channels (in the matrix of C_{mn}, $n=100$) to select from, but most of these links have only their preferred few channels to choose from due to the learning process. This is the reason why a large percentage of channel weights are equal to *1* as we preset the channel weight values to *1* in the channel weight table and only a few channels are being used for a certain link.

Figure 8-11 illustrates that the reinforcement learning process of a link on channel selection can benefit from the increase of the usage level of the link. It can be seen that some channel weight values are constantly being rewarded for certain links since those link usages are also increasing along with the time as shown in Figure 8-10. It is also worth mentioning that from event *300* to event *600* which is the period when the network suffers a large amount of concurrent transmissions due to the extremely high traffic load condition (*37* concurrent traffic flows), some channels are punished for particular links due to their high utilization level as a link with high utilization level not only can explore good channels but also can detect the bad channels which are occupied by its neighbour links thanks to the channel sensing technique. Consequently, through the learning process, links with a high utilization level can easily avoid using bad channels in the future which reduces the potential hidden node problem and improves the channel spatial reuse.

This further proves the theory we proposed in Chapter 7, that the cross-layer design of combining cognitive greedy-back haul (CGB) routing with reinforcement learning based channel assignment scheme (RLCAS) can have the highest learning impact on channel selections as CGB relays traffic through the backhaul links with a high link usage. In other words, those backhaul links have better knowledge of the network environment with respect to the channel spatial reuse. In addition, the learning rate of links with a heavy usage rises exponentially with event time thanks to the greedy link selection methodology used by CGB.

8.5 Conclusion

In this chapter, we have compared the reinforcement learning based channel assignment scheme (RLCAS) with the assistance of sensing to the reinforcement learning based channel assignment scheme without sensing (RL-NS-CAS) as well as a pure sensing based channel assignment scheme in terms of delay, end-to-end throughput and time sharing probability in a multi-hop network scenario in combination with cognitive-greedy backhaul routing (CGB). The results show that the network performance can significantly benefit from using learning-based channel assignment schemes rather than a pure sensing scheme due to their capability of reducing the impact of the hidden node problem. This chapter also examined the learning process on channel selection from various angles, such as traffic load, link location and link usage. The link usage is generally dependent on the link location and network traffic pattern. Results show that the more opportunity the link can get, the better chance it has to explore the network environment to find its most suitable channels as well as most interfered channels. This indicates the CGB routing metric outperforms the other routing metrics mentioned in this thesis due to its greedy routing behaviour.

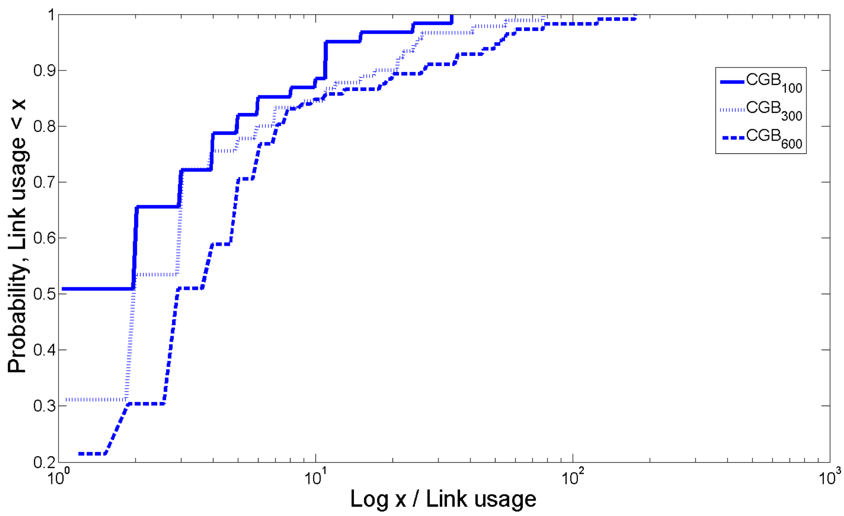


Figure 8-10 CDF of link usage at varying event time under traffic load of *37* flows

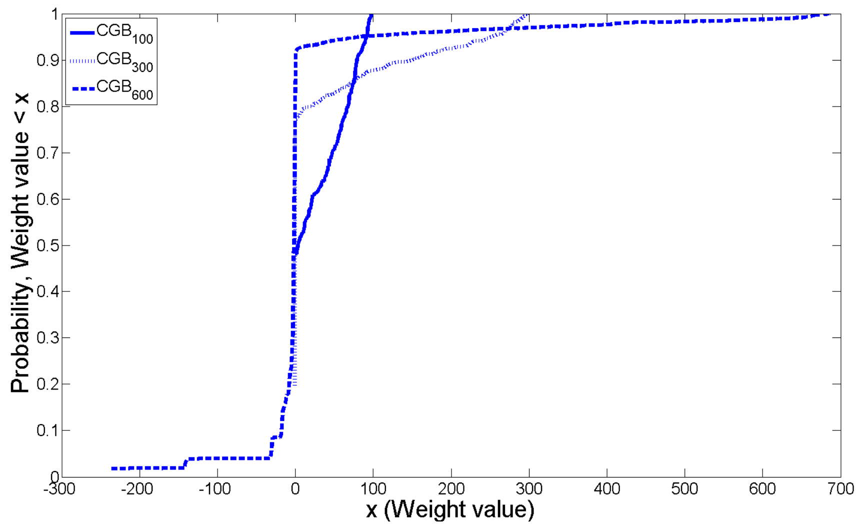


Figure 8-11 CDF of channel weight value at varying event time under traffic load of *37* flows

Chapter 9

9 Further Work

Contents

Many of the proposed routing protocols and metrics are aimed at improving wireless ad hoc network performance such as network capacity, protocol overheads, interference, throughput, delay, energy consumption and network lifetime in order to make wireless ad hoc networks more practical. However, these network parameters can be improved comparatively easily when the network topology is fixed rather than dynamic. Node mobility and the dynamic features of network topology have to be considered with the routing design, otherwise the wireless ad hoc network loses its main advantages over other types of wireless network in most scenarios.

This chapter presents a detailed description of potential further research work that is related to the current work of this thesis, including modifying the wireless ad hoc network scenario to include mobility, the requirements of a cognitive routing protocol, performance optimization with the assistance of directional antennas and power control, accounting for more environmental factors in cognitive routing metric design, and further studies on the reinforcement learning based channel assignment scheme.

9.1 The Effect of Node Mobility on Wireless Ad Hoc Routing

In this thesis, investigations about network performance have been carried out under a static network topology where nodes have no mobility. However, in practical wireless ad hoc networks, node mobility has to be considered in both routing metric and protocol designs. It is expected that both traditional routing protocols and proposed routing metrics will not cope well with frequent topology changes which result in varying connectivity conditions among the terminals. Therefore, to achieve more realistic cognitive routing in wireless ad hoc networks, routing metric and protocol design should be designed to adapt to traffic and propagation conditions as well as the mobility patterns of the mobile network nodes.

9.2 Cognitive Routing Protocols

All investigations in this thesis have largely focused on the design of the routing metrics, with little emphasis on the implementation and improvement of the protocols operating with such metrics. For example, the overhead of implementing the different routing metrics has not been fully investigated. Although we described the fact that proactive routing protocols are more suitable than reactive routing protocols for dynamic routing metric design in Chapter 2, they are not the best solution for saving network bandwidth while each node can retain the network topology by periodic updating. One solution would be a cognitive routing protocol, in which by using a machine learning algorithm, each node can either adjust its periodic updating frequency based on its activity and past experience for the proactive type or predicts future conditions and intelligently/selectively floods routing updates through predicted strong links rather than all links for the reactive type.

9.3 Network QoS Optimization

In order to further improve wireless ad hoc network QoS in terms of capacity, throughput, delay, channel blocking/dropping probability, energy consumption and interference, other techniques should be investigated in association with cognitive routing such as the use of directional antennas, power control and clustering.

Use of directional antennas has been proposed as a hot technique to reduce channel interference from unwanted sources as it can radiate greater power in one or more directions. Wireless ad hoc network capacity can be significantly improved by using directional antennas as they aim to improve channel spatial reuse by reducing interference to other users as well as increasing the signal to the intended receivers.

Power control is another technique that can increase SINR and spectral efficiency as well as data rate by increasing transmitter power. However, raising transmit power also raises the interference level to the other receivers and the higher power consumes more energy. Network performance can be further improved if power control is associated with the cognitive concept as each node can adjust future transmit power based on past information of interference it suffered in order to maximize SINR at the receivers and minimize interference to other transmitters.

Clustering techniques in wireless sensor networks have been proposed as an efficient way to reduce energy consumption and prolong the lifetime of the network, such as the LEACH [89] and HEED [90] protocols. In a cluster based network, cluster heads can gather information from nodes in their cluster group, and are interconnected to generate a communication backbone to transmit the aggregated data to the sink node. In this way, energy use and network lifetime can be improved by turning off the redundant relaying nodes and retaining the minimum number of activated nodes.

9.4 Enhanced Multi-hop Reinforcement Learning Based Channel Assignment

In Chapter 7 and 8, we observed that the reinforcement learning based multi-hop channel assignment scheme (RLCAS) can increase the channel spatial reuse by reducing the hidden node problem through the learning process. Time sharing probability has been reduced more by using RLCAS compared with other channel assignment schemes. Further research can be investigated on the reinforcement learning algorithm in order to enhance the channel assignment scheme.

For example, consider the scenario shown in Figure 9-1. Here, a link *B* chooses the same channel as link *A* with a zero weight value on the channel, and the channel can be utilized for link *B* as the receiver of link *B* (*Rx2*) is far away from the transmitter of link *A* (*Tx1*), but the channel cannot be used for link *A* any more as the receiver of link *A* (*Rx1*) is close to the transmitter of link *B* (*Tx2*). Therefore, although link *A* starts to punish the weight value on the channel and link *B* starts to increase the weight of that channel, both links will use the same channel for a period time until link *A*'s weight value on this channel becomes smaller than the weight value on other channels. This period can be quite a while if the channel has been used and rewarded for a long time for link A (giving an enormous weight value for that channel) before the link B's activation, due to the same level of reward (*+1*) and punishment values (*-1*) we applied in this thesis. In order to reduce the period that both links use the same channel, we can apply different punishment factor level compared with the reward factor level, e.g. reward is *+1* and punish can be *-3* or divide the previous weight value by *0.5* to allow the learning to adapt quicker with environmental changes.

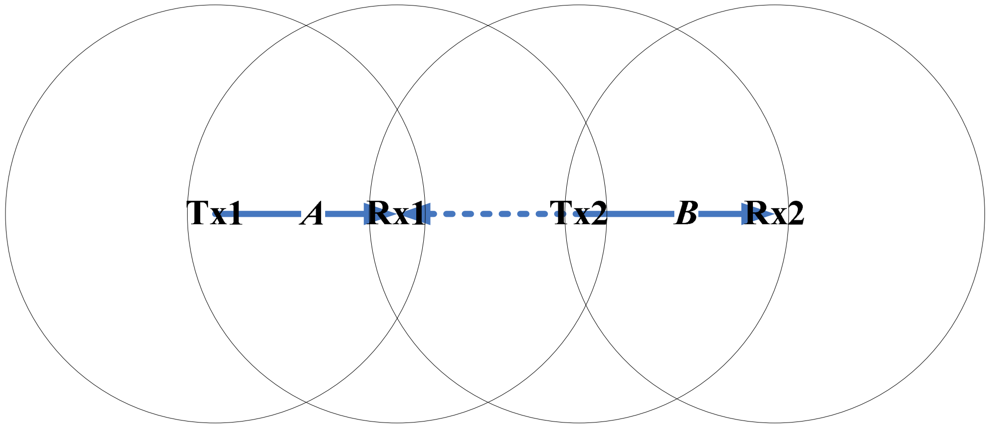


Figure 9-1 Example of hidden node problem

9.5 Multipath Routing

Multipath routing is a routing technique that uses multiple flows instead of single path routing between the end hosts to improve bandwidth, transmission reliability and load balancing [91, 92]. The technique proposes that the traffic can be distributed and carried by multiple simultaneously available paths, so that the available bandwidth can be better utilized by using multiple active transmission tasks especially under low traffic load conditions. It also provides a better fault tolerance for the system as if a path fails; only the stream assigned to this path is affected, the other paths can still maintain their transmissions continuously [93, 94].

Chapter 10

10 Summary and Conclusions

Contents

10.1 Summary and Conclusions of the Work

This thesis has explored the design of cognitive routing metrics and cross-layer techniques for wireless ad hoc networks in order to reduce the relaying burden while still maintaining network capacity. A brief summary and conclusion of the entire thesis is presented below. More detailed and specific summaries are provided at the end of each chapter. In addition, the main findings of the research and the original contributions to the field are also highlighted in this section.

After a general introduction in Chapter 1, Chapter 2 presents a detailed literature review on wireless ad routing metrics. In this chapter, two different types of routing metrics are categorized as non-link quality based (MIR, shortest path, PARMA etc.) and link quality based (e.g. ETX, ETT, WCETT). A comprehensive discussion on why the cognitive concept is important for wireless ad hoc routing metric design has been provided. In addition, the chapter also discusses a few routing protocols to help the reader to understand the wireless ad hoc routing process as a whole, and the most suitable type of routing protocol has been discussed for this type of research work. Dijkstra's algorithm is presented as it is the approach for all proposed routing metric designs in the thesis to find the shortest path due to the lowest weight cost along the path.

Chapter 3 looks at modelling techniques and validation methods. A Monte Carlo simulation technique has been selected, with MATLAB software used to perform the simulation task. Several chosen performance measures and verification methods are introduced for system performance analysis, including number of disturbed nodes, congestion level, end-to-end bottleneck capacity, throughput, delay, energy consumption, time sharing probability and channel weight.

Chapter 4 presents the early work carried out for wireless ad hoc routing metric design in order to make the routing metric more 'cognitive' by taking the surrounding node number into account. Initially, a MIR routing metric is proposed as it is the inspiration for the proposed routing metric design in this chapter. The proposed disturbance/inconvenience based routing metric (DIR) not only can take the outward interference (disturbance) into account like MIR, but also can take inward interference (inconvenience) into account. Furthermore, DIR is modified to DIR^k and DIR_{th} which can modify the value of the link weight to the power of *k* and separate nodes into different groups based on their disturbance and inconvenience level respectively. Those modifications make the routing metric more cognitive as they can control the weight value by adjusting the *k* value or the threshold value.

A detailed capacity model is provided in Chapter 5 with a discussion of the importance of end-to-end bottleneck capacity. A capacity based routing (CBR) metric is first presented for the purpose of the proposed routing metric design for bottleneck-aware routing (BAR), as BAR is inspired by CBR. The routing metric design BAR is more cognitive compared with CBR and shortest path as it not only takes node capacity into account but is also aware of the location of end-to-end bottleneck nodes in order to improve end-to-end bottleneck capacity. The results show that end-to-end bottleneck capacity is improved by using BAR under low traffic conditions.

Chapter 6 introduces a novel routing metric design, cognitive greedy-backhaul (CGB), which aims to reduce relaying hops when establishing a path while avoiding creating end-to-end bottleneck nodes by assigning additional channels to congested links. CGB takes cross-layer information into the routing metric design as the link weight depends on the number of channels that are assigned to the link. A multi-channel environment is introduced in the chapter and a number of simple channel assignment schemes are initially proposed to study the impact of the proposed routing metric design. Results show a significant increase in the end-to-end throughput by using CGB compared with the other routing metrics such as shortest path and available capacity routing.

In Chapter 7, CGB is further studied in a more practical network model which includes a path loss model, practical interference model, file length based traffic model (instead of the on-off based traffic model used for early chapters) and an energy model. By using the cognitive radio concept, a reinforcement learning based channel assignment scheme (RLCAS) is also provided to associate with CGB to deliver a better cross-layer design as channels can be assigned cognitively through the learning process. Results show that the cross-layer design of combining CGB with the reinforcement learning based channel assignment scheme (RLCAS) outperforms the other schemes in network energy consumption, delay and end-to-end throughput.

Chapter 8 studies the learning process of RLCAS when associated with CGB. Other channel assignment schemes are also investigated to illustrate why channel assignment can benefit the learning engine when combined with our CGB routing metric. Results show that RLCAS with CGB can reduce the hidden node problem compared with other schemes, thanks to the learning.

10.2 Original Contributions

Much of the work on wireless ad hoc routing designs by other researchers has concentrated on routing protocols. This thesis instead has focused on investigating the impact of relaying by examining cognitive routing metrics and network design that exploits the network environment, including nodes/links that are required to assign variable amounts of bandwidth using cognitive radio and cognitive network techniques. The original and novel contributions of the work presented in this thesis can be categorized into three distinct areas of work. The major contributions are summarized below.

10.2.1 Cognitive Routing Metric Designs

- A new family of interference based routing metrics – disturbance/inconvenience based routing (DIR) have been developed. Much of the work on interference routing metrics by other researchers has concentrated only on taking the inward interference of the object node in order to mitigate the interference level it suffers. Our DIR can control the degree of 'inconvenience' and 'disturbance' by adjusting the interference priority factor as the metric takes into account the combination of node inward and outward interference (Chapter 4). The DIR based routing metrics can become selfish by changing the priority factor to account for inconvenience only as the node only calculates the interference it receives; the metrics also can become altruistic if nodes only calculate the disturbance. Intuitively, cognitive radio networks can also benefit by applying these types of routing metrics as primary users can be more selfish and secondary users should be altruistic. These contributions have been published in [95].

- In Chapter 5, bottleneck-aware routing (BAR) is introduced. The novelty of this routing metric is aimed at building routes to enhance the overall network capacity as well as the end-to-end bottleneck capacity. Although other routing metrics (CBR [53], DLAR [65] and HMP [66]) have been carried out to improve capacity and load balancing, to the best of the author's knowledge, no such routing metrics are aimed to improve capacity while also optimising end-to-end performance in heterogeneous networks where there are a wide variety of node types and capabilities (e.g. low, medium and high capacity nodes).

- A cognitive-greedy backhaul (CGB) routing metric is introduced in Chapter 6. In this routing metric, the weight value of the link is determined by its channel utilization level. In this way, routes can be established in a more cognitive approach as the routing metric takes account of the other local issues of the channel condition. There are other routing metrics which use the cross-layer information as their metric weight function. In [55], Zhao proposes a routing metric PARMA which takes physical-layer link speed and MAC-layer channel congestion into account. Although PARMA uses cross-layer information to avoid links with low data rates and high retransmission rates due to a busy medium, it does not take path stability and path length into the metric design. Rather than taking the channel conditions into the routing metric design, CGB explores the channel utilization level that is based on a network traffic perspective in order to build stable paths with minimum relaying burden by exploiting cross-layer information. Work from this chapter has been published in [96].

10.2.2 Cross-layer Design

The concept of using channel assignment conditions as a routing metric function has been shown to be an efficient way for a cross-layer design to improve the performance of wireless ad hoc networks. In [97], Iannone proposes a cross-layer approach so that the routing level can find paths that offer low levels of generated interference, reliability in terms of Packet Success Rate and higher available transmission rate. Our cross-layer approach is combining CGB routing with several practical channel assignment schemes, such as reinforcement learning based (RLCAS) and sensing based (SCAS). Rather than designing a cross-layer approach to optimize the routing choices, our cross-layer design associates the channel assignment scheme with the routing metric, in order to reduce the relaying burden while still maintaining network capacity in various traffic conditions. This work has been described in Chapters 7 and 8.

- In Chapter 7, the reinforcement learning based channel assignment scheme (RLCAS) has been examined by applying several routing metrics. The novelty of these schemes is to explore the learning efficiency for RLCAS when associating the routing metric design with multi-hop networks.

- In Chapter 8, cross-layer designs combining CGB routing with various channel assignment schemes have been investigated. The learning process of using each channel assignment scheme is examined from various angles (such as traffic load, link location and link usage). This chapter also explains why the CGB routing metric can enhance the learning process of RLCAS.

10.2.3 Analytical Tools and Modelling

Unlike Gupta and Kumar's paper [12] where the achievable throughput of a node is estimated as an information theoretic limit, our capacity model is developed by considering the relaying burden impact generated by various routing metric designs. The model has been developed to predict the lower bound capacity in terms of path length, transmission range, traffic load, maximum channel capacity and spatial channel reuse factor in Chapter 7. In addition, Chapter 7 also proposed a time sharing scheme in order to calculate the throughput and delay performance without consideration of a particular MAC scheme.

Appendix A - Publications

Bo Han, David Grace, Paul Mitchell, ***A Cognitive Cross-layer Design for Wireless Ad Hoc Networks***, Submitted to Ad Hoc Networks Journal, 2011.

Bo Han, David Grace, Paul Mitchell, ***Exploring Reinforcement Learning Channel Assignment with Cognitive Routing for Wireless Ad Hoc Networks***, in preparation for IET Communications, 2012.

Bo Han, David Grace, and Paul Mitchell, ***Cognitive Greedy-Backhaul Routing Metric Exploiting Cross-layer Design for Wireless Ad Hoc and Mesh Networks***, presented at Cognitive Radio Oriented Wireless Networks & Communications (CROWNCOM), 2010.

Bo Han and David Grace, ***Using Cognitive Interference Routing to Avoid Congested Areas in Wireless Ad Hoc Networks***, presented at Proceedings of 18th International Conference on ICCCN 2009.

Bo Han, David Grace, and Paul Mitchell, ***Using Bottleneck Aware Routing to Improve End-to-End Bottleneck Capacity for Wireless Ad Hoc Networks***, presented at Karlsruhe Workshop on Software Radios (WSR), Karlsruhe, Germany, March, 2010.

Glossary

AODV	Ad hoc On-Demand Distance Vector Routing
DSR	Dynamic Source Routing
DSDV	Destination-Sequenced Distance-Vector Routing
DIR	Disturbance/Inconvenience Based Routing
DIR^k	Disturbance/Inconvenience Based Routing to The Power of k
$DIR_{threshold}$	Disturbance/Inconvenience Based Routing Based on Threshold
BAR	Bottleneck-Aware Routing
CGB	Cognitive Greedy-Backhaul
RL	Reinforcement Learning
RLCAS	Reinforcement Learning Based Channel Assignment Scheme
MANET	Mobile Ad Hoc Network
WSN	Wireless Sensor Network
WMN	Wireless Mesh Network
WPR	Wireless Routing Protocol
FSR	Fisheye State Routing
OLSR	Optimized Link State Routing Protocol
TORA	Temporally-Ordered Routing Algorithm
ABR	Associativity-Based Routing
ARA	Ant-Colony Based Routing Algorithm
ZRP	Zone Routing Protocol
ETX	Expected Transmission Count
ETT	Expected Transmission Time
WCETT	Weighted Cumulative Expected Transmission Time
ENT	Effective Number of Transmissions
SDR	Software Defined Radio
MIR	Minimum Impact Routing
CBR	Capacity Based Routing
MAC	Media Access Control
DN	Disturbed Node
PARMA	PHY/MAC Aware Routing Metric

MIC	Metric of Interference and Channel-switching
iWARE	Interference Aware Routing Metric (IWARE)
mETX	Modified Expected Number of Transmissions
CTT	Interference Clique Transmission Time
CATT	Contention-Aware Transmission Time
MCR	Multi-Channel Routing
QoS	Quality of Service
IR	Interference Range
TR	Transmission Range
SH	Shortest-path by Hops Routing Metric / Minimum Hoc Count
SINR	Signal to Interference plus Noise Ratio
SCAS	Sensing based Channel Assignment Scheme
LOS	Line of Sight
BPSK	Binary Phase Shift Keying
BER	Bit Error Rate
ILR	Interference Level Based Routing
CDF	Cumulative Distribution Function
DCA	Dynamic Channel Assignment
RL-NS-CAS	RL without Sensing based Channel Assignment Scheme

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