

STOCHASTIC MODELING OF ROUTING PROTOCOLS FOR COGNITIVE RADIO
NETWORKS

By

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ABSTRACT

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Cognitive radios are expected to revolutionize wireless networking because of their ability to sense, manage and share the mobile available spectrum. Efficient utilization of the available spectrum could be significantly improved by incorporating different cognitive radio based networks. Challenges are involved in utilizing the cognitive radios in a network, most of which rise from the dynamic nature of available spectrum that is not present in traditional wireless networks. The set of available spectrum blocks (channels) changes randomly with the arrival and departure of the users licensed to a specific spectrum band. These users are known as primary users. If a band is used by a primary user, the cognitive radio alters its transmission power level or modulation scheme to change its transmission range and switches to another channel. In traditional wireless networks, a link is stable if it is less prone to interference. In cognitive radio networks, however, a link that is interference free might break due to the arrival of its primary user. Therefore, links' stability forms a stochastic process with OFF and ON states; ON, if the primary user is absent. Evidently, traditional network protocols fail in this environment. New sets of protocols are needed in each layer to cope with the stochastic dynamics of cognitive radio networks.

In this dissertation we present a comprehensive stochastic framework and a decision theory based model for the problem of routing packets from a source to a destination in a cognitive radio network. We begin by introducing two probability distributions called ArgMax and ArgMin for probabilistic channel selection mechanisms, routing, and MAC protocols. The ArgMax probability distribution locates the most stable link from a set of available links. Conversely, ArgMin identifies

the least stable link. ArgMax and ArgMin together provide valuable information on the diversity of the stability of available links in a spectrum band. Next, considering the stochastic arrival of primary users, we model the transition of packets from one hop to the other by a Semi-Markov process and develop a Primary Spread Aware Routing Protocol (PSARP) that learns the dynamics of the environment and adapts its routing decision accordingly.

Further, we use a decision theory framework. A utility function is designed to capture the effect of spectrum measurement, fluctuation of bandwidth availability and path quality. A node cognitively decides its best candidate among its neighbors by utilizing a decision tree. Each branch of the tree is quantified by the utility function and a posterior probability distribution, constructed using ArgMax probability distribution, which predicts the suitability of available neighbors. In DTCR (Decision Tree Cognitive Routing), nodes learn their operational environment and adapt their decision making accordingly. We extend the Decision tree modeling to translate video routing in a dynamic cognitive radio network into a decision theory problem. Then terminal analysis backward induction is used to produce our routing scheme that improves the peak signal-to-noise ratio of the received video.

We show through this dissertation that by acknowledging the stochastic property of the cognitive radio networks' environment and constructing strategies using the statistical and mathematical tools that deal with such uncertainties, the utilization of these networks will greatly improve.

To my parents, Reza and Afsaneh.

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PREFACE

Should the answer not satiate my ambition

Leave me to my sword, and my battle ground.

Hakim Abul-Qasim Ferdowsi Tusi(940 1020 CE)

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Chapter 1

Introduction

Advances in technology and development of new wireless devices increase the need for better utilization of spectrum bands. The number of unlicensed spectrum bands are limited and according to FCC, up to 85% of licensed spectrum bands is wasted when the licensed users are not using their dedicated spectrum band. Cognitive radio networks (CRN) are developed to solve the under-utilization problem of licensed spectrum bands.

Cognitive radios make use of not only their own available band, but also the vacancies of other user's bands. The cognitive radio interrupts its transmission upon the arrival of the other users. Since the transmission is subjected to licensed (primary) user's random interruptions, the communication environment is stochastic. Protocols should be designed to cope with the stochastic behavior of primary users and include the uncertainty in the availability of spectrum in their implementation. In traditional wireless networks, a link is stable if it is less prone to interference. In cognitive radio networks, however, a link that is interference free might break due to the arrival of its primary user. Therefore, links' stability forms a stochastic process with OFF and ON states; ON, if the primary user is absent. Evidently, traditional network protocols fail in this environment. New sets of protocols are needed in each layer to cope with the stochastic dynamics of cognitive radio networks. The new MAC and routing layer protocols should consider the stability of a link because each time the communication fails, packets are lost. In addition, radios restart the handshaking process, which increases communication overhead and severely damages the performance

in terms of throughput and delay. By using a routing protocol that guides the packets through the paths with higher probability of stability than others, CRNs throughput and delay will substantially improve. With acknowledging CRNs' true nature and using probability and stochastic theory tools, we can develop protocols that nicely adapt to any uncertainty in the communication environment.

In order to identify a channel that has the highest probability of stability, we need to use the statistical observations of channels availabilities and develop a probability distribution describing the channels stabilities. Therefore, we introduce two probability distributions called ArgMax and ArgMin, that are able to identify the most and the least stable channels. These probability distributions have broad applications in cognitive channel selection mechanisms, routing and MAC protocols. The ArgMax probability distribution locates the maximum random variable among a set of random variables, while the ArgMin locates the minimum random variable. The ArgMin probability distribution has a variety of applications and is shown to be useful in achieving a lower bound on the network's minimum spectral capacity. To show an application of the proposed probability distributions, a Probabilistic Selection Routing Procedure (PSRP) is designed to guide packets in a mesh CRN operating in a densely populated urban area. In PSRP the path is constructed step by step based on the localized random decision of each node. Selection probabilities are assigned to each neighbor node and evaluated periodically using the ArgMax probability distribution according to the available usage time of a channel.

Next, we extend PSRP into a Primary Spread Aware Routing Protocol (PSARP). The proposed *Primary Spread Aware Routing Protocol* (PSARP) is based on nonhomogeneous Markovian transitions that give priority to the paths with the minimum expected frequency presence of primary users. The PSARP selects the next hop probabilistically. The probability of selection depends on both the next hop's ability to transfer a packet to a particular destination and also the stability of the links connecting it to the sender node. A Primary Weight Measure (PWM) is used in assessing

the next hop ability to transfer packets to its own intermediate neighbor. PWM is constructed using both ArgMax and ArgMin distribution and identifies the diversity of spread of channels around a particular node, the sender node is able to estimate the stability in the network environment beyond its next hop neighbor. Therefore, nodes are able to divert their traffic through the paths that are less frequently affected by primary users. The PSARP is designed as an adaptive per-hop routing scheme to quickly adapt to changes in the dynamic CRN environment and is successful to do so based on our simulation results.

Finally, considering the basic definition of routing that decides among possible routes, and the intrinsic property of cognitive radio networks that is the uncertainty of available resources, we use decision theory to construct a more advance routing mechanism. In decision theory a player plays against nature, meaning the player opponent does not try to increase its fortune, but exhibits stochastic performance that is explained by probability laws. Decision theory address decision making problems in an environment where uncertainty exists and the true state cannot be fully predicted. This is exactly the situation of a cognitive radio sender. First, the variety of spectrums and their corresponding channels provide multiple routes from the server to the client. Hence, the server has multiple options with different routing consequences. Second, the chosen route might not stay stable during the transmission period. Therefore, the sender node is uncertain about the consequences of its decision. In other words, the circumstances governing a node's decision might change. The Decision Tree Cognitive Routing (DTCR) scheme is able to predict the dynamic of the network environment and routes the client packets to a server that operates in a heavily populated urban area. To accommodate the needs of video applications, the DTCR is extended into a Video Cognitive Routing (VCR) scheme that finds the best downlink route when video packets are traversing from a server to a client.

In summary, this dissertation investigates the problem of routing in *dynamic cognitive radio*

networks. Specifically, by considering the CRNs' uncertainties, we introduce two frameworks, a stochastic framework and a Decision theory based framework, to study the dynamics of CRN. Our objective is to (1) provide a more accurate decision making tool to capture the stochastic behavior of primary users in CRNs, and (2) maximize throughput and consequently packet loss by proposing routing procedures that captures the uncertainties and adapts to variations accordingly.

1.1 Overview of Contributions

We summarize the contribution of this dissertation as follows:

- Identification of the most stable channel is crucial in decision making of MAC and routing protocols in CRN. Therefore, we introduce the ArgMax and ArgMin probability distributions and show their application in probabilistic channel selection mechanisms, routing, and MAC protocols. In almost all of the probabilistic approaches designed for multi-channel-multi-hop networks such as the work of Song et al [2] and Cui [3], the well-known probability distribution Odds-On-Mean (OOM) is used to evaluate the selection probabilities. In OOM probability distribution the probabilities are proportional to the population mean. However, the ArgMax distribution locates the largest variable (in terms of magnitude) in a set of random variables. Therefore, the ArgMax probability distribution is more suitable in modeling probabilistic behavior than OOM in network systems. Replacing the OOM probability distribution by the ArgMax probability distribution in many probabilistic selection mechanisms improves their performance significantly. The main functionality of the ArgMin probability distribution is to locate the random variable that at an instant is the minimum of a set of random variables. Therefore, ArgMin probability distribution has variety of applications in networks. For instance, the minimal spectral capacity can be identified using the ArgMin

probability distribution. Using the ArgMax and ArgMin probability distributions, we introduce an interesting measure called *primary weight measure*, that indicates the frequency and the nature of the distribution of primary users around a particular node. A low value of the primary weight measure metric indicates uniform and frequent primary users interruptions on the channels surrounding a node. With this information MAC and routing decisions are taken more efficiently.

- By acknowledging the stochastic behavior of CRNs, we develop a stochastic model of a mesh CRN in a densely populated urban area. In our model, the number of available nodes, channels and the available usage time are random. Through this analysis, we formulate the available usage time of each channel in a spectrum with a truncated distribution. Next, a Probabilistic Selection Routing Procedure (PSRP) is proposed to guide packets in the CRN. The superiority of ArgMax is shown by evaluating the performance of the PSRP adopting ArgMax and OOM as its selection probabilities. We further, extend the PSRP and develop a Primary Spread Aware Routing protocol (PSARP). PSARP is able to adapt to the uncertainties of spectrum availability in cognitive radio networks. PSARP is based on the Markovian property of a particular flow from a source to a destination and uses PWM as one of its routing metrics. We demonstrated through simulation that PSARP is robust to the variation of the primary users' activity. Our results confirm that using a stochastic protocol for a stochastic environment is indeed more suitable than using deterministic protocols. We believe this research is the beginning of a new line of work on the development of stochastic routing protocols.
- We proceed to adopt the techniques in statistics that address decision making problems in an environment where uncertainty exists and the true state cannot be fully predicted. Hence,

we construct the Decision Tree Cognitive Routing (DTCR) scheme. By adopting the decision problem components, we construct appropriate sample and posterior distributions to explain the status of channels and nodes in supporting packet delivery. We also introduce a utility function that captures the effects of spectrum availability, bandwidth fluctuations and path quality. This utility function is expandable to include other important decision making factors. Our results show that DTCR is successful in maintaining the network throughput near the optimal value and works significantly better than the AODV-based routing schemes designed for dynamic cognitive radio networks.

- Transferring video applications over dynamic cognitive radio networks is challenging due to the variation in bandwidth availability and the stability of the available bands. Therefore, we use the decision theory components and expand on DTCR to develop a Video aware Cognitive Routing scheme (VCR). We model and analyze the problem of downlink routing of video packets in a dynamic CRN. The previous sample and posterior distributions are now modified to explain the status of channels and nodes in supporting video frames quality of service. The performance of DTCR and VCR is compared with the most acceptable class of the previous dynamic routing strategies for CRNs with implementing the protocols on the real time network simulator.

1.2 Organization of The Dissertation

The rest of this dissertation is organized as follows. Chapter provides the background on the cognitive radios and cognitive radio networks as well as an overview of the related work that has been done on the design and implementation of routing protocols. In Chapter , the definition of the ArgMax and the ArgMin probability distributions is presented. In addition, we introduce

the PWM routing metric that is made by combining these two probability measures. In Chapter the stochastic modeling of a cognitive radio mesh network that leads to development of PSRP is introduced. We show the usage of the ArgMax and the ArgMin probability distribution in PSRP through simulation. In Chapter , the stochastic routing protocol PSARP is presented that routes the packets in a CRN operating in a highly dynamic environment. The concept of decision theory and DTCR is presented in Chapter . We show that by using the decision theory components, one could utilize the cognitive abilities of CR nodes to design routing strategies adaptive to the dynamic nature of cognitive radio networks. Chapter demonstrates how VCR is developed from the basis of DTCR. At the end of each chapter a summary of the comparison results is presented. Finally we highlight the possible future directions of this dissertation in Chapter .

Chapter 2

Background

This chapter presents the background on the development of cognitive radios and cognitive radio networks. The dynamics of cognitive radio networks are discussed, which led the development of new sets of protocols at different network layers. Related work on routing protocols in network layer of cognitive radio networks is also presented in this chapter.

2.1 Development of Cognitive Radios

The idea of cognitive radio was first introduced by Joe Mitola in 1991, “a radio that is aware of its spectral environment as well as its user and network environment”. Traditional radios were built on a fixed platform. Gradually, advances in digital communication transformed the analog design to a programmable digital radio. Radio use could be flexible by modifying the software with no hardware development.

Figure 2.1 shows a continuum of the software defined radio technology. The very first generation of these radios are software capable radios. These radios have fixed modulation capabilities, relatively small number of frequencies, limited data and data rate capabilities, and the ability to handle data under software control. They emerged into software programmable radios, new functionalities could be added through software changes and their advance network capabilities. The next generation of these radios are software defined radios (SDR). By FCC definition a SDR is

a communications device whose attributes and capabilities are developed and/or implemented in software [4]. In SDR systems, there is complete adjustability through software of all radio operating parameters. To reach the vision of Mitola, sensors are added to SDRs that collect information, such as chemical surroundings, geolocation, time of day, biometric data, or even network quality-of-service (QoS) measures. These type of radios are aware radios. The aware radios do not use the collected information and are simply aware of the changes. In the adaptive radios, frequency, instantaneous bandwidth, modulation scheme, error-correction coding, channel mitigation strategies (e.g., equalizers or RAKE filters), system timing (e.g., a TDMA structure), data rate (baud timing), transmit power, and even filtering characteristics and operating parameters are adapted based on the sensory measurement. Finally cognitive radios (CR) were developed. In this class of radios, sensors create awareness of the environment and actuators interact with the environment. The CR has the ability to create a model of the environment that includes state or memory of the observed events. The CR has a learning capability that helps to select specific actions or adaptations to reach a performance goal.

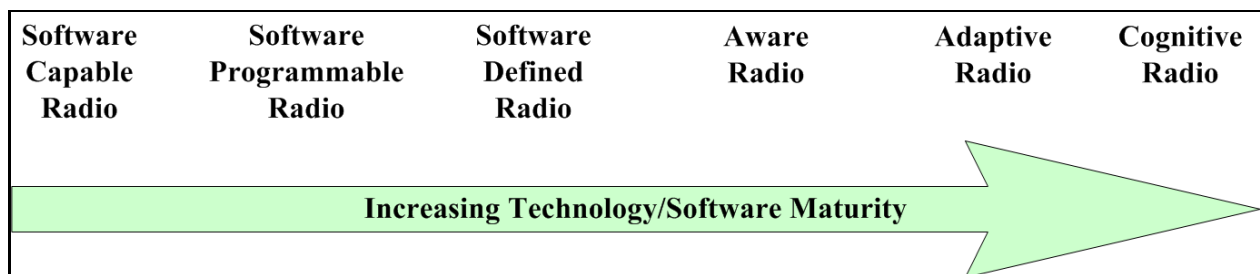


Figure 2.1 Software-Defined Radio Technology Continuum. [1].

For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this thesis dissertation.

The very first CRs were modeled in the Defense Advanced Research Projects Agency (DARPA) NeXt Generation (XG) radio development program. The spectrum environment is sensed, the unoccupied portion is identified. These radios rendezvous in the unoccupied band, communicate

in that band, and vacate the band if a legacy signal reenters that band. [1].

2.2 Cognitive Radio Architecture

The cognitive radios are built on top of SDR platforms. The cognitive radio platform is shown in Figure 2.2. The cognition engine sits on top of the software unit that controls the tunable parameters in the hardware unit. The hardware is similar to other next generation radios (SDR, adaptive radios). The main difference is in the processor that contains the cognition engine and a set of computational modules. The modules have Radio Knowledge Representation Language (RXML) frames. RXML provides a standard language within which unanticipated data exchanges can be defined dynamically. The radio itself, including the equalizer, in the context of a comprehensive ontology, is written in RXML.

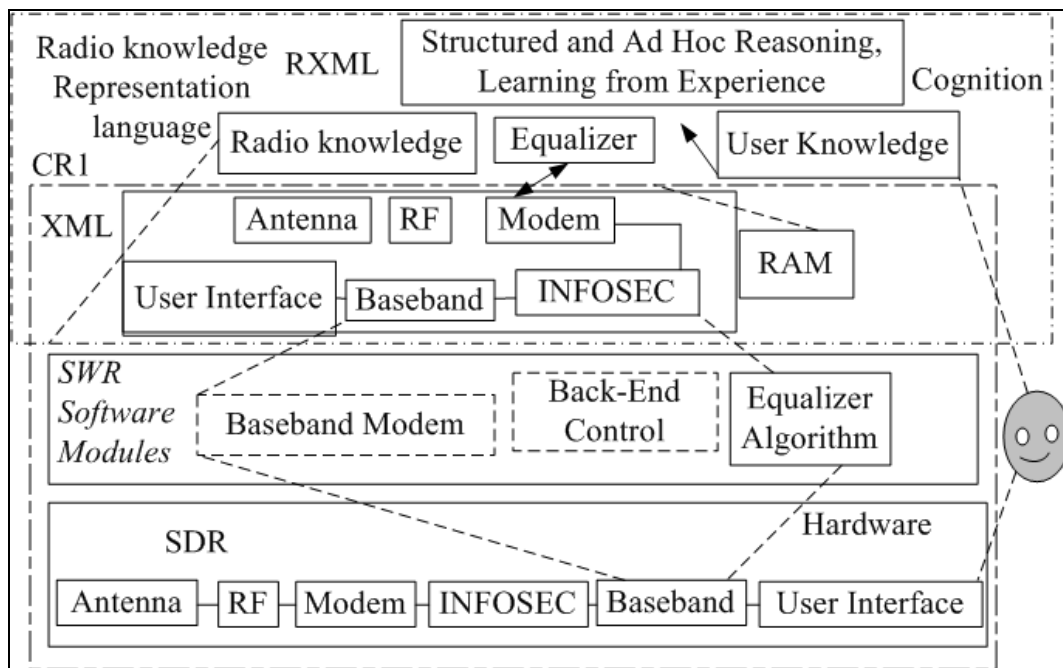


Figure 2.2 CR platform; computational intelligence and learning capabilities are added to SDR platform [1].

Each of the following functional components should be in place in order to have a complete

cognitive radio. Some are developed and some are still under development. A minimal cognitive radio architecture should have the following functional components:

- User interface, which includes haptic, acoustic, and video sensing and perception functions.
- Environmental sensor functions that sense environmental characteristics such as temperature, location, etc.
- SDR functions, which includes radio frequency sensing and software defined radio applications.
- Cognition functions; system control, planning and learning.
- Local effector functions; text, graphics and multimedia displays.

A CR node follows through the following cycle to command its effector unit for appropriate action. It first observes the environment and gathers the sensory measurement. After this stage, the Orient phase starts, which determines how significant is an observation. In this phase the CR creates a short term memory of its observed data and after analyzing its short term memory, it saves the important reading in its long term memory. Information manipulation is still an important topic in the CR research. A CR then follows a plan to decide about its reaction to a certain stimuli. Finally using effector modules, it initiates a selected process according to its plan.

Nokia Research Center, Qualcomm and the XG technology INC, are the leading research and development companies in cognitive radio technology. XG technology developed a new line of products called Xmax systems, which includes “line of high-performance access points, fixed and mobile personal WiFi hotspots, mobile switching centers (MSC’s) as well as network management and deployment tools. XG’s unique and patented protocol outperforms WiFi, WiMax and traditional cellular technologies like LTE in shared and interference prone radio bands”. [5]. Currently

different SDRs are commercially available that can be used in experimental test beds such as SDR MK1.5 'Andrus' [6], USRP1 and USRP2 [7].

2.3 Cognitive Radio Networks

Cognitive radio networks are built with networking the CR nodes together. Researchers have two categories for such networks: Network of Cognitive Radios (NCR) and Cognitive Networks (CN). In the first category each node focuses on its own requirements and changes its parameters according to its individual needs. In such networks, the end-to-end goal of the network might be achieved as it is investigated by Neel, et al. [8] through game theory. However, these networks are not actively perusing the end to end goals of the network. CNs on the other hand are the networks that cognitively adapt their parameters to reach a set of predefined goals. The common feature between these two categories is that the CR nodes functionalities should be extended to encompass the entire network stack. The architecture of a cognitive radio node is shown in Figure 2.3. The communication system includes the network layer stack. The end to end goals are defined by the user domain. They could be end-to-end network requirements such as the quality of service or delay. The cognitive engine is the core of the device. It performs the modeling, learning, and optimization processes necessary to reconfigure the communication system in order to achieve the goals. Information such as radio frequency (RF) and environmental data that could affect system performance are gathered by the radio domain. The policy engine checks and controls the solutions to follow the regulations set by the network administrators and federal communication policies. A cognitive radio follows a loop of self-explanatory components: Observe, Orient, Decide and Act, to reach the requirements of wireless communication from its own perspective and network perspective. Here, we elaborate on observable parameters (Meters) at each networking layer and

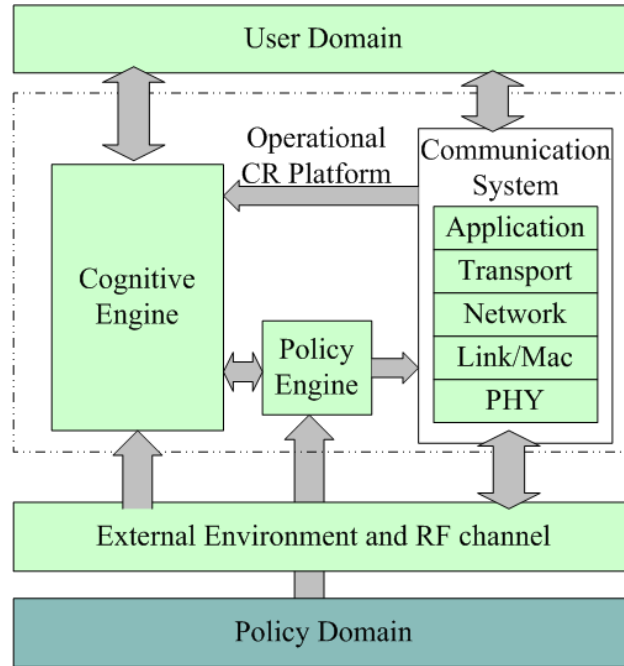


Figure 2.3 CR architecture with a cognitive engine connected to the network protocol stack and a policy engine that checks the support ability of the hardware in response to the commands of the cognitive engine [1].

the corresponding control mechanisms (Knobs) that can improve the communication process. We also present the cognition cycle that takes place by observing different parameters at each layer.

2.3.1 Knobs and Meters

The CR senses its environment and needs to be aware of the major factors that affect its communication. The environmental and communication factors could be directly observed by CR's sensors or conceived from previous measurement. The observable parameters at the different layers of the network are called meters. By observing and comparing the meters with their desired value, control parameters (knobs) are adjusted by the embedded protocols. Table 2.1 summarizes meters and knobs at each network layer.

The cognitive engine requires four levels of awareness to make its decision: (1) recognizing the needs of the user, (2) understanding the limitations imposed on the radio operation by the

Table 2.1 Knobs and Meters by layer [1]

Layer	Meters(Observable parameters)	Knobs(Writable parameters)
NETWORK	Packet delay Packet jitter	Packet size Packet rate
MAC	Cyclic redundancy check (CRC) Automatic repeat request (ARQ) Frame error rate Data rate	Source coding Channel coding rate and type Frame size and type Interleaving details Channel/slot/code allocation Duplexing Multiple access Encryption
PHY	Bit error rate (BER) Signal-to-noise ratio (SNR) Signal-to-interference and noise ratio (SINR) Received signal strength indicator (RSSI) Pathloss Fading statistics Doppler spread Delay spread Multipath profile Angle of arrival (AOA) Noise power Interference power Peak-to-average power ratio Error vector magnitude Spectral efficiency	Transmitter power Spreading type Spreading code Modulation type Modulation index Bandwidth Pulse shaping Symbol rate Carrier frequency Dynamic range Equalization Antenna beam shape

channel and external environment, (3) realizing its own limitations in flexibility and power, and (4) conforming to local regulations and policy. This is achieved by observing multiple meters related to each category of awareness.

Advances in technology are bringing the vision of mixing intelligence with communication into reality. This vision was first pictured by Claude Shannon. The CRs are the intelligent radios that require a new set of protocols to communicate with each other. Protocols that have the ability to

change different knobs in relation to the variations observed from multiple meters at the same time. Traditional network protocols do not make use of the intelligence of CRs and therefore downgrade them to an ordinarily wireless transmitter and receiver. For CRs to work to their full capacities, network protocols should be fully adaptive to the changes made by cognitive engine.

Besides handling the unexpected changes due to the intelligent decision making of the device, the operational environment of CRNs are very different from traditional wireless networks. In such networks once a channel is available for a network node, it could use that channel without interruption as long as it continues to transmit. In CRNs, radios are intelligent enough to make use of not only their own available bandwidth but other's available bands. Vacancies of other user's bands are exploited and a CR interrupts its transmission upon the arrival of the users. A stochastic communication environment is created when the transmission is interrupted by the random arrivals of other users. Protocols should be designed to cope with stochastic behavior of users and include the uncertainties involved in their design. The MAC and routing layer protocols should consider the stability of a band, since failing to make the right decision would severely damage the performance of such networks. In the next section we introduce how CRs rendezvous to different bands and elaborate more on the stochastic nature of CRNs and possible solutions in protocol design.

2.4 Spectrum Sharing

Cognitive radios have the ability to sense the available spectrum and identify whether it is being used by other users. Their cognition engine can decide whether a sensed idle portion of a spectrum in terms of frequency, time and space could be used. Two CRs could rendezvous at an unoccupied channel and communicate. Traditional wireless networks use a dedicated spectrum band (channel) for their communication. When the network users are inactive, a large portion of spectrum is

wasted. The advance sensing ability of CRs opens a possibility to have a network consists of CR nodes that only use the white space of spectrum to communicate. This will substantially improve the existing spectrum utilization. The CRs that only use the white space spectrum are called Secondary Users (SU). These users should interrupt their transmission on a specific band if a licensed user of that band comes back. The licensed user is also referred to as Primary User (PU). A CR should be able to observe the presence of primary and secondary users. Moreover, for reliable communication, the received signal and interference to noise ratio (SINR), current connectivity, packet delays and the state of other nodes' parameter choices (power, channel selection, location) also need to be observed and communicated with other nodes.

For a successful rendezvous in a CRN, multiple SUs must dynamically sense large number of channels to identify vacancies. In addition, for two radios to establish a link, control messages need to be exchanged among the users. The problem of rendezvous is obviously not trivial. Approaches for rendezvous could be classified into two main categories: aided and unaided. The aided rendezvous is infrastructure-based, meaning the information regarding the channel availability are periodically broadcasted by a server. The server may also be a clearinghouse for link establishment and the scheduling of transmissions. As it can be perceived from its name, in unaided rendezvous each CR finds another node in the network by its own. In this type of rendezvous, a dedicated control channel may or may not exist. Using a single control channel might result in a single point of failure in large networks. Therefore a distributed solution in which different cluster of nodes use different control channels, can be adopted. Another approach allows the control messages to use data channels. As a result, all channels could be used as control channels. The process of establishing a link without a control channel is called blind rendezvous. In an infrastructure-based network, a control channel is used to identify spectrum availability. In the architecture proposed by Buddhikot, et al. [9], some frequencies are selected for use as spectrum information channels. A

wireless interface is dedicated by clients to scan these channels to broadcast information regarding spectrum availability from the base-stations. Control channels are also used by clients to send the beacon messages requesting the use of an available channel. Clearly, the use of a common control channel simplifies the process of rendezvous. However, if multiple base-stations and associated radios are in close vicinity of one another, they all compete to use the control channel. As the users are quite diverse, possibly covering all wireless users, some regulators worry about how to resolve the potential contention. The policy engine of CR nodes needs to be equipped with appropriate rules, preventing unfair allocation of the control channel, giving priority based on service providers' advantages in order to encourage them to invest in CR technology.

In most of the work on multi channel medium access control in decentralized networks, the control packet information is also sent on a dedicated control channel. They assume nodes equipped with two radios [10]. One radio constantly monitors a dedicated control channel and by sending request-to-send (RTS) and clear-to-send (CTS) frames uses that channel to reserve transmission on one of the potential data channels. The second radio tunes to the reserved data channel for the exchange of data frames. This approach simplifies the rendezvous problem but as the network size increases, the control channel acts as a bottleneck. If the control channel is congested, the operation of the entire network fails. A possible solution is to have multiple control channels. The disadvantage is that the presence of PUs may not be sensed correctly that raises the issue of fairness.

When there is no dedicated control channel (blind rendezvous), all channels are potentially available for the exchange of control and data. The set of channels must be sensed in random on pre established order for possible availability. The radios then need to send beacons and wait for responses to make a connection with other users. A possible solution for blind rendezvous is described in Horine and Turgut [11]. Radios take turns and access the channel in time slots. If

the radio does not sense other users (PU or SU) in its vicinity, it sends a beacon message followed by a period of silence to receive a response from a potential receiver. Two existing methods by which the radios can eventually meet in the same channel are random rendezvous and sequence based rendezvous. In random rendezvous, a radio wishing to join a network visits the potential communications channels in random order. Sequence-based rendezvous was proposed by DaSilva and Guerreiro [12] in which predefined sequences used by each radio arranges the potential channels in their visiting order. The idea is that both transceivers follow the same sequence, although arbitrarily delayed with respect to each other.

For a successful and efficient transmission between two SUs, not only the rendezvous solutions should be robust to the dynamic spectrum occupation but also take into consideration the stability of an available channel. If two CRs establish a connection following one of the rendezvous solutions, and shortly after they start sending the data frames, the connection is torn down due to return of a primary user, a substantial amount of network resources will be wasted. Large delay caused by reestablishing a link will make the network useless for a wide range of applications. Since CRs have the memory and the intelligence, the probabilistic approach is the promising solutions to overcome this problem.

Undeniably, CRNs structure falls under the framework of stochastic systems. With acknowledging their true nature and using the probability and stochastic theory tools we can develop protocols that nicely adapt to any uncertainly and randomness exists in the communication environment. For instance, observing the history of the meters variations and using statistical methods to assign selection probabilities to potential channels would substantially reduce the possibility of connection interruption. Recently probabilistic approach is being used in MAC physical layer but simplistic probability models are being adopted. In this dissertation we introduce a probability model that points to most stable channel with higher accuracy than the commonly used probability

model.

The medium access strategies are extensively under investigation. However, less attention is made to the design of routing protocols for CRNs. In this dissertation, after introducing a new probability distribution to find the most stable path, design of routing protocols in stochastic environment is discussed. The routing protocols proposed in this dissertation use the learning capabilities of CR to select the appropriate route.

2.5 Use of Decision Theory and Game Theory in CRN

In cognitive radio networks, secondary users are intelligent and act to optimize their performance. They aim at maximizing their own benefits. Therefore, Game theoretic models are preferred. game theory analyzes the strategies that decision makers can take in interacting with one another in order to optimize their gain. As the definition suggests, by adopting game theory tools one is able to obtain useful strategies in spectrum sharing and routing. The components of spectrum sharing games in cognitive radio networks are described as follows: Players are the secondary users that compete for the unlicensed spectrum band. Actions are the transmission parameters, such as transmission power level, access rate, etc. Payoff (Utility) is a non-decreasing function of the QoS by utilizing the spectrum. The games are divided into the following main categories:

- Non-cooperative games and Nash equilibria
- Economic games, auction games and mechanisms design
- Cooperative games
- Stochastic games

Efficient distributed approaches for dynamic spectrum sensing is derived by adopting non-cooperative game theory. Neel et.al [13] and Giupponi et.al [13], present useful applications of this adaptation in CRN. Economic games and cooperative games are also adopted in CRN as explained in [14]. However, one important aspect of CRN is overlooked in these schemes. The spectrum opportunities and the surrounding radio environment keep changing overtime. Therefore, for a dynamic environment, we cannot assume that the stage of the game is constant. However, this is the major assumption in the first three game categories mentioned above. A stochastic game that is an extension of Markov Decision Process [15] is a better fit for designing MAC and routing strategies in dynamic CRNs. In a stochastic game, after the players select and execute their actions, the game moves to a new random state with transition probability determined by the current state and one action from each player. Meanwhile, at each stage each player attempts to maximize an objective function. The objective function is the expected sum of the payoffs over an infinite horizon. The solution is called policy and is a probability distribution over action set at any state. Stochastic game is used in transmission control, anti-jamming defense and spectrum auction. However using stochastic game for routing is a challenge because the players should have complete knowledge about the game being played. Meaning secondary users in a dynamic CRN should have a complete knowledge of the available routes and the other secondary and primary users. The game should be divided into stages so that the secondary users obtain some information about the others actions and payoffs.

An alternative to game theory is statistical decision theory. Pratt, Raiffa and Schlaifer in [16] explain that a problem of decision making under uncertainty can be addressed by using statistical decision theory. The problem should have the following characteristics:

1. A choice, or in some cases, the sequence of choices must be made among various course of actions.

2. The choice or sequence of choices will ultimately lead to some consequence, but the decision maker cannot be sure in advance what this sequence will be because it depends not only on his choice or choices but on an unpredictable event or sequence of events.

It is clear from the above characteristics that this associates well with situation of secondary users when deciding their route in a dynamic CRN. First, a secondary user has multiple choices (different links and routes) for routing. Second, the secondary user cannot be sure whether the chosen route will stay stable to transfer its packets to the ultimate destination. The advantage of using decision theory is that we assume that the player is playing against nature meaning the player opponent does not try to increase its fortune, but exhibits stochastic performance that is explained by probability laws. In decision theory the current state of the game is taken to be uncertain and the decisions are made considering such uncertainties. In a highly dynamic environment, decision theory leads to less computational complexity than game theory since many types of games have multiple equilibria under such variations. Using the learning capability of cognitive radios we modeled the problem of routing in CRN into a decision problem and obtained satisfactory improvement in the performance of the network. To the best of our knowledge, this is the first time that statistical decision theory is adopted to model the problem of routing in dynamic CRN.

The problem of routing in CRN falls under a class of decision problem that is concerned with the logical analysis of choices among various course of actions. For this class of problem, (a) the consequence of any course of action depends on the state of the world s , (b) the true state (the correct route) is as yet unknown, (c) it is possible to obtain some information about the true state by conducting an experiment e at a cost, and observing the outcome z of the experiment. The basic assumption is that the preference of the decision maker does not change. This means his judgment about the outcome z of each potential experiment is consistent with his preference of the consequence of his choice. His preference is presented by a utility function u and his judgment is

sealed in terms of a probability measure P .

Here we introduce some definitions and notations that are used in these class of problems in decision theory.

State space $\mathcal{S} = \{s_1, s_2, \dots\}$: Set of possible states (choices) available to the decision maker.

Action space $\mathcal{A} = \{a_1, a_2, \dots\}$: Variable a_i is the act of choosing state s_j to visit.

Set of experiments $\mathcal{E} = \{e_0, e_1\}$: When the decision maker performs a test to get some information in support of an act. Experiments are classified by e_0 and e_1 , where e_0 stands for no experiment and e_1 is to perform an experiment or test to support a right act. The experiment e_1 gives rise to possible samples $\mathcal{Z} = \{z_1, z_2, \dots\}$, z_i is a sample observation that is in favor of a state s_i .

Sample distribution $P(z|s)$: In statistics samples and measurements are subject to false readings, therefore although samples are informative, but are not 100% reliable. Sample distribution $P(z|s)$ governs this probabilistic situation: it gives the probability of observing sample z whenever s is the true state. For s to be a true state means that it is the right and the most appropriate state. Sample distribution is used in quantifying our observation in indeterministic environment.

Prior distribution $P(s)$ is assigned to the state space \mathcal{S} . An appropriate prior distribution is based on the history of availability of a state and usually does not reflect current status of states. Posterior distribution $P(s|z)$: The probability of observing the state s when the sample observation is z . This measure indicates the possibility of choosing a true state s by observing a sample observation z . This probability is found using the conditional probability formula

$$P(s|z) = \frac{P(z|s)P(s)}{\sum_s P(z|s)P(s)}. \quad (2.1)$$

Note that the denominator in the above equation is the marginal distribution of sample observation.

In analyzing a decision problem a diagram known as decision tree is used. The tree demonstrates different paths of reaching a state by performing or not performing an experiment and following different acts as shown in Figure 2.4. In any decision problem there is a loss/gain associated with a decision. When the decision maker makes a decision to perform an experiment e (relies on the sampling probabilities $P(z|s)$), it pays a cost and in return gains extra knowledge on the possible consequence of his decision. Therefore, the utility function $U(e, z, a, s)$ is assigned to the decision data (e, z, a, s) .

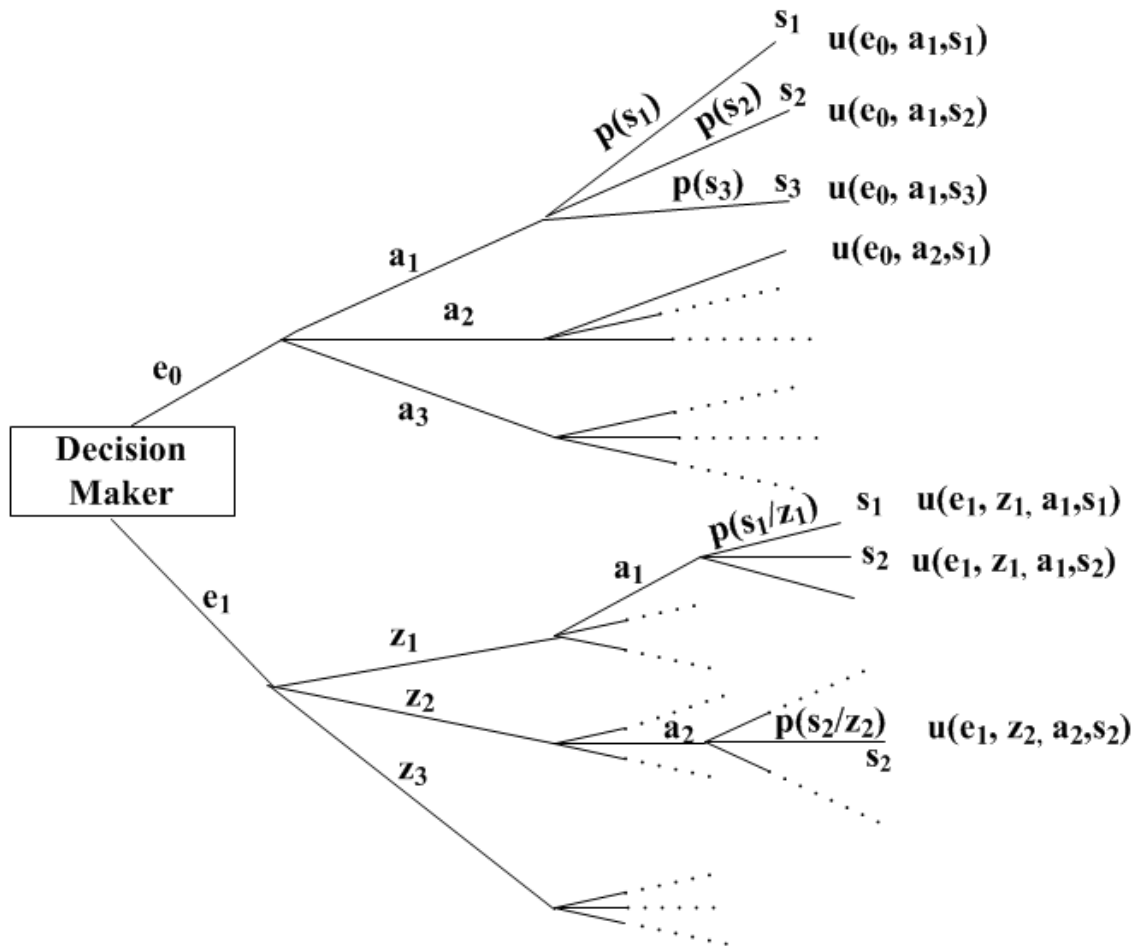


Figure 2.4 Decision tree with states $\{s_1, s_2, \dots\}$, actions $\{a_1, a_2, \dots\}$, and posterior distributions $P(s|z)$.

The utility function u indicates the decision maker gains or losses. Decision data is usually denoted by (e, z, a, s) . The decision maker runs experiment e , observes sample z , takes act a when the true state is indeed s . An optimal act minimizes the expected loss or maximizes the expected gain; the later is $\max_e E_{p(z|e)}[\max_a [E_{p(s|z,e)} U(e, z, a, s)]]$.

In Chapter we present the details of modeling routing in a dynamic CRN using the decision theory concepts mentioned above. In the following sections we categorize the routing protocols developed for cognitive radio networks and provide an overview on their design.

2.6 Static and Semi-dynamic Routing Protocols

Developing routing protocols for wireless mesh networks has been investigated for years. With the development of new technologies, more advanced routing schemes could be designed and implemented. The importance of routing in CRN is greatly dependent on the behavior of PUs. Long absence of PUs categorizes the CRN as a static multi-channel-multi-hop network and the traditional routing protocols are applied. When the PU's behavior is more dynamic, new approaches in routing are necessary. Zhu et al. [17] propose a spectrum based routing protocol that simplifies the collaboration between spectrum decision and route selection by establishing a spectrum tree at each spectrum band. They assume that the statistics of PU's activities and available spectrum band information can be obtained by existing spectrum sensing and sharing techniques. In [18] the authors develop a routing protocol called SAMER, which offers a set of candidate routes to the destination. The actual forwarding path opportunistically adapts to the dynamic spectrum conditions and exploits the link with the highest spectrum availability at the time. In [19], authors propose a new metric based on the probabilistic definition of link available capacity into the cost of the Dijkstra-like algorithm. Researchers such as Wu et al. [20] propose a distributed multi-channel

and routing assignment in heterogeneous multi radio multi-channel-multi-hop wireless networks where the channel coordination and route selection is based on the information exchanged among two hop neighbors. In [21], authors allow each network node to exchange their spectrum opportunity information and select the optimal channel. The network learns the behavior of PUs via a nonparametric statistical learning method based on past observations. In the work of Cui et al [3] and Song [2], a probabilistic approach is introduced in which the OOM distribution is used to assign the selection probabilities for every path.

ROSA-PMQ is designed for video or multimedia applications in semi-dynamic environment [22]. It is a cross layer protocol that jointly does the routing, spectrum assignment, scheduling and power assignment functionalities. Khalife et al. [19] propose a joint routing and channel selection scheme to fulfill bandwidth requirements of flows. Jashni et al. [23] propose a routing scheme with channel selection to support multimedia application in which the probability of channel selection of neighbor SUs is evaluated using the game theory fictitious play technique. Xie et al. [24], Gao et al. [25], and Xie and Xi in [26] propose routing schemes to support multicast communication in CRNs. In Chapter , we present our scheme that focuses on the unicast transport of video application packets in a highly dynamic environment.

2.7 Dynamic Routing Protocols

As mentioned in the previous section, by incorporating cognitive radios, the wireless network possesses new dynamics and many researchers started to design new routing protocols accordingly. Among those are the works of [17], [18] and [27]. They model the spectrum utilization as a new metric to enhance the selection mechanism in traditional routing schemes. In [28], [29] and [30], the problem of routing, scheduling and interference awareness is formulated into different forms

of an optimization problem. These studies' underlying assumption is that the behavior of primary users is fairly predictable. The protocols we propose on the other hand, considers a dynamic environment and takes into account the stochastic behavior of CRNs.

Many of the proposed routing schemes for dynamic CRNs adopted the framework of ad hoc or wireless sensor networks. The uncertainty in the links' availability is mapped into the unavailability of nodes in the above networks. Hence, protocols such as SODV [31], CODV [32], OSDRP [33] and [34] are proposed. In fact, the nature of instability in ad hoc or sensor networks is very different from CRNs. Links' availability is unpredictable in CRNs and the repetition of calling a route discovery mechanism in such protocols would increase the delay and degrade the overall throughput. Previous studies mainly focus on reliable routing of video or multimedia applications that require a certain quality of service in semi-dynamic environment. How et al. [33] propose OSDRP, a quality of service aware routing protocol for dynamic environment that adopts the frame work of AODV protocol.

In DTCR, we take a decision theory approach that gives a solution for decisions that need to be made under uncertainties. A relatively close approach is game theory. Pavlidou and Kolsidas [35] surveyed different routing protocols for wireless communication networks designed by the game theory framework. These studies, however have static spectrums and channels. Nurmi [36] uses a dynamic Bayesian game to form a dynamic stage game with incomplete information. Our decision theory approach also uses the Bayesian rule to construct the posterior distributions in order to include the effect of cognitive radio dynamics. In [14], the authors summarize the applications of game theory in cognitive radio networks. In the work of Zhu et al. [37], nodes are grouped into layers similar to our work. They also use a game theory framework with an end-to-end path utility to route the secondary users' control messages in a pilot channel. Cacciapuoti et al. [38] develop a theoretical model to analyze the opportunistic routing procedures. Our framework uses cognitive

decision making to make its selection an opportunistic routing scenario.

The DTCR is different from the above since it uses the decision theory framework and a decision tree to model a decision strategy for a node. We construct sample and posterior distributions to explain the status of channels and nodes in supporting packet delivery. These distributions use a simple metric such as channel availability duration. However, they can be easily extended to use advance metrics such as OPERA, proposed by Caleffi et al. [39]. There is no central agent helping in decision making; the nodes try to estimate the future uncertainties and choose neighbor nodes that maximizes their expected gain.

2.8 Cross Layer Design

As explained in section 2.3.1, we need to combine different meters from different layers to achieve a performance goal. Therefore, at first glance, it might be plausible to adopt the cross layer approach and use the previously designed cross layer protocols for cognitive radio networks. To take into account meters of different layers, originally researchers combine two layer's meter (physical and MAC layer) but this would optimize one objective in the expense of other objectives. Recently, a new kind of cross layer design is proposed. CrossTalk [40], ECLAIR [41], CLD [42] and the framework of Gong et al. [43] propose using a parallel structure that acts as a shared database accessible to whichever layers choose to use it. The cognitive network design however, is taking a different approach. They use the cognitive process that would consider not only the network goals but also learns from its past behaviors. Use of learning and proactive adaptation is included in cognitive radio networks. The protocols at each layer should be modified to include the learning and adaptation processes.

We propose two new probability distributions ArgMax for the selection probabilities, and

ArgMin to find minimal spectral capacity. The proposed distributions is not only limited to the probabilistic routing but also could be used in probabilistic MAC layer techniques. We develop two routing mechanism. First, PSARP that is specifically designed for nondeterministic dynamical systems. In PSARP, we design a stochastic-based routing to locate the best route in a stochastic environment using stochastic systems tools. We observed that the transition of packets from a source to a destination in a cognitive radio network is a stochastic process since the random arrival of primary users on channels make the next state of the system (next hop) in the path indeterministic. PSARP adapts to the change of behavior of network dynamics and selects the next node based on the uncertainty of channel existence. Second, the DTCR that is developed using decision theory components to deal with decision making under uncertainties of cognitive radio networks environment.

In the following chapter we elaborate more on the stochastic modeling of cognitive radio networks and the proposed routing schemes.

Chapter 3

ArgMax and ArgMin: Transitional

Probabilistic Models in Cognitive Radio

Mesh Networks

Random phenomena are present in any realistic system. Many parameters in computer networks are random and follow a certain distribution. It is often of interest to find the maximum or the minimum element of these random variables. The parameters could be channel occupancy, queue capacity, packets arrival and departure rate, delay, etc. The main functionality of the ArgMax (ArgMin) probability distribution is to locate the random variable that at an instant is the maximum (minimum) of a set of random variables. In this chapter, we present the definition of the ArgMax and ArgMin distributions. We also develop a new metric called Primary Weight Measure (PWM) to capture the uniformity or diversity of availability in the channels of different spectrum bands. In other words, PWM shows how the primary users affect the channels around a particular node. If all the channels are affected uniformly by primary users, then all channels provide the same utilization for a secondary node and there is no priority in selecting one channel over another. Moreover, if a node has the highest PWM, it has at least one channel that is minimally affected by primary users. In subsequent chapters, we elaborate on the application of the proposed distributions and the PWM metric in cognitive radio network.

3.1 ArgMax and ArgMin distributions

Let Z_1, \dots, Z_n be a finite sequence of continuous random variables defined on a probability space. We let $Z_{\max} = \max\{Z_i, i = 1, \dots, n\}$. The corresponding ArgMax random variable τ_{\max} indicates the index of the random variable that attains the maximum values. Precisely, $(\tau_{\max} = i) = (Z_{\max} = Z_i)$, for $i = 1, \dots, n$. A probability distribution of τ_{\max} , $\{p(1), p(2), \dots, p(n)\}$, is called the ArgMax distribution which is unique because of the continuity of the random variables Z_1, Z_2, \dots, Z_n . Therefore

$$p(i) = P\{\tau_{\max} = i\} = P\{Z_{\max} = Z_i\}, \quad i = 1, \dots, n. \quad (3.1)$$

The corresponding ArgMin random variable τ_{\min} indicates the index of the random variable that attains the minimum values. Therefore

$$q(i) = P\{\tau_{\min} = i\} = P\{Z_{\min} = Z_i\}, \quad i = 1, \dots, n. \quad (3.2)$$

Theorem 1. *The ArgMax and ArgMin probability distribution for an array of independent continuous random variables Z_1, \dots, Z_n with distribution functions F_1, F_2, \dots, F_n are respectively given by*

$$p(i) = \int_{-\infty}^{+\infty} \left[\prod_{j=1, j \neq i}^n F_j(z) \right] dF_i(z), \quad i = 1, \dots, n. \quad (3.3)$$

$$q(i) = \int_{-\infty}^{+\infty} \left[\prod_{j=1, j \neq i}^n 1 - F_j(z) \right] dF_i(z), \quad i = 1, \dots, n. \quad (3.4)$$

Proof. The theorem will be easily proven by conditioning on $Z_i = z$, using the law of total

probability and the independence assumption.

$$\begin{aligned}
p(i) &= P\{Z_{\max} = Z_i\} = \int_{-\infty}^{+\infty} p(Z_1, Z_2, \dots, Z_n < z | Z_i = z) dF_i(z) \\
&= \int_{-\infty}^{+\infty} \left[\prod_{j=1, j \neq i}^n p(Z_j < z) \right] dF_i(z), \quad i = 1, \dots, n.
\end{aligned} \tag{3.5}$$

□

We prove directly in the following lemma that $\{p(1), p(2), \dots, p(n)\}$ given in (2) is indeed a probability distribution.

Lemma 1. Assume $p(1), p(2), \dots, p(n)$ are given by (2), then

$$p(1) + p(2) + \dots + p(n) = 1.$$

Proof. Let $U(x) = \prod_{j \neq i} F_j(x)$ and $dv(x) = f_i(x)dx$. Then $dU(x) = \sum_{k \neq i} f_k(x) \prod_{j \neq i \neq k} F_j(x)$, and $V(x) = F_i(x)$. Therefore it follows from integration by parts that

$$p(i) = \left[\prod_j F_j(x) \right]_0^\infty - \sum_{k \neq i} \int_{-\infty}^{+\infty} \left[\prod_{j \neq k} F_j(x) \right] f_k(x) dx = 1 - \sum_{k \neq i} p_k.$$

Therefore $\sum_{j=1}^n p(j) = 1$

□

Following the same reasoning, the validity of the ArgMin probability distribution is also proven.

The odds-on-mean probability distribution, the well-known probability distribution that is used

in most probabilistic channel selections and routing, is defined as follows.

$$\phi(i) = \frac{\mu_i}{\sum_{i=1}^n \mu_i}, \quad (3.6)$$

where $\mu_i = E(Z_i)$, $i = 1, \dots, n$. In our application $\mu_i \geq 0$.

The distribution of state space probabilities of odds-on-mean is different than the ArgMax distribution. In the following subsection we demonstrate this difference through an example, where the random variable Z follows an exponential distribution.

3.2 Exponentially Distributed Random Variables

We let S_t denote the class of all subsets of $\{1, 2, \dots, n\}$ that contain exactly t nonidentical members, $t = 1, \dots, n$.

Theorem 2. *Let Z_1, \dots, Z_n be independent exponentially distributed random variables with parameters $\lambda_1, \dots, \lambda_n$. Then the following holds:*

a. The ArgMax probability distribution is given by

$$\begin{aligned} p(n) = & 1 + \sum_{i=1}^{n-1} \frac{\lambda_n}{\lambda_n + \lambda_i} - \sum_{\{i,j\} \in S_2} \frac{\lambda_n}{\lambda_n + \lambda_i + \lambda_j} \\ & + \sum_{\{i,j,k\} \in S_3} \frac{\lambda_n}{\lambda_n + \lambda_i + \lambda_j + \lambda_k} + \dots \\ & + (-1)^n \frac{\lambda_n}{\lambda_n + \lambda_1 + \lambda_2 + \dots + \lambda_{n-1}}. \end{aligned}$$

b. The ArgMin probability distribution is given by

$$q(i) = \frac{\lambda_i}{\sum_{j=1}^n \lambda_j}.$$

To derive the probability distribution $p(1), \dots, p(n)$, apply Theorem 2 using the transformation $\pi_i(j) = j - i$, for $j > i$, and $\pi_i(j) = n + j - i$, for $j \leq i$, and rearrange the set of the parameters $\lambda_1, \dots, \lambda_n$ to

$$\{\lambda_{i+1}, \dots, \lambda_n, \lambda_1, \dots, \lambda_{i-1}, \lambda_i\}.$$

Special Cases: Let $n = 3$. Then

$$\begin{aligned} p(1) &= 1 - \frac{\lambda_1}{\lambda_1 + \lambda_2} - \frac{\lambda_1}{\lambda_1 + \lambda_3} + \frac{\lambda_1}{\lambda_1 + \lambda_2 + \lambda_3}, \\ p(2) &= 1 - \frac{\lambda_2}{\lambda_2 + \lambda_1} - \frac{\lambda_2}{\lambda_2 + \lambda_3} + \frac{\lambda_2}{\lambda_1 + \lambda_2 + \lambda_3}, \\ p(3) &= 1 - \frac{\lambda_3}{\lambda_3 + \lambda_1} - \frac{\lambda_3}{\lambda_3 + \lambda_2} + \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3}. \end{aligned}$$

In terms of $\mu_i = \frac{1}{\lambda_i}$

$$p(1) = 1 - \frac{\mu_2}{\mu_1 + \mu_2} - \frac{\mu_3}{\mu_1 + \mu_3} + \frac{\mu_2 \mu_3}{\mu_1 \mu_2 + \mu_1 \mu_3 + \mu_2 \mu_3}.$$

For $\mu_1 = 1$, $\mu_2 = 2$, $\mu_3 = 3$, $p(1) \simeq \frac{1}{8}$, while $\phi(1) = \frac{\mu_1}{\mu_1 + \mu_2 + \mu_3} = \frac{1}{6}$. Therefore, we see that the ArgMax distribution could be substantially different from the odds-on-mean distribution.

3.3 Primary Weight Measure

The primary weight measure is a metric with nonnegative values. It is developed to capture the uniformity or diversity in spectrum bands available to a secondary user. Small values of PWM indicate uniformity while large values of PWM indicate diversity. The PWM metric is evaluated by measuring the distance between the two probability distributions: ArgMax and ArgMin.

The ArgMax probability distribution points to the channel that at an instant of time appears to have the maximum idle frequency. Assume a node i is connected to j via a set of N_t available channels at time t . A channel between node i and j is stable if it is less prone to the arrivals of primary users. We let $u_{ij}[k, t]$ be the random variable that represents the link (i, j) utilization via channel k at time t ; defined as the average frequency that a channel, sensed by the node i , is available without any interruption from primary users. We suppress the time index t from our notation whenever there is no ambiguity. In our simulation, we record the number of times that a channel is sensed idle over a period of time and then use it for $u_{ij}[k]$. The probability that the channel n between node i and j has the maximum utility is modeled by the ArgMax probability distribution as follows:

$$p_{i,j}(n) = Pr\{k^* = n\} = Pr\left\{u_{ij}[n] = \max\{u_{ij}[k], u_{ij}[k] \in E[i, j : t]\}\right\}, \quad (3.7)$$

where k^* is the channel between nodes i and j with maximum utilization at time t , and $E[i, j; t]$ is the set of all available channels between nodes i and j at time t .

Following the same analogy the ArgMin measure points to the channel that is less stable and is highly exposed to the presence of primary users. Therefore, the probability that the channel h

between node i and j has the minimum utility is

$$q_{i,j}(h) = Pr\{k^* = h\} = Pr\left\{u_{ij}[n] = \min\{u_{ij}[k], u_{ij}[k] \in E[i, j : t]\}\right\} \quad (3.8)$$

where k^* is the channel between i and j with minimum utilization at time t . More comprehensive definitions of ArgMax and ArgMin probability distributions is presented in the Appendix.

Monitoring the ArgMax and ArgMin probability distributions provides interesting information on the utilization of channels. If the primary users arrive frequently, the channels will be affected almost uniformly by the primary users arrival. Therefore, the probability that a channel n has the maximum idle frequency is close to the probability that the same channel has the minimum idle frequency. Therefore the difference between $p_{i,j}(n)$ and $q_{i,j}(n)$ is small. Large gap between the two probability distribution p and q imply a nonuniform spread of primary users on channels; and hence, there exists a channel whose utilization is substantially larger. We measure the distance between the distribution functions ArgMin and ArgMax by the Kullback-Leibler divergence (K-L) [44] measure.

The K-L divergence is a non-symmetric measure of the difference between two probability distributions h and g . In probability theory, h represents the “true” distribution of data, observations, or a precisely calculated theoretical distribution. The distribution g represents a theory, model, description, or approximation of h . It also can be interpreted as the opportunity lost for implementing g instead of h . The K-L divergence for two discrete probability distributions h and g is defined to be

$$D_{KL}(h||g) = \sum_k h(k) \log \frac{h(k)}{g(k)}. \quad (3.9)$$

It requires that $g(k) > 0$ for all the values of k for which $h(k) > 0$. It possesses the properties that

- $D_{KL}(h||g) \neq D_{KL}(g||h)$.
- $D_{KL}(h||g) \geq 0$.
- $D_{KL}(h||g) = 0 \Leftrightarrow h = g$.

In the context of a cognitive network, with $h = p_{i,j}$, $g = q_{i,j}$, and channel utilization as the average frequency that a channel is idle without any interruption from primary user, we have the following interpretations for the K-L divergence.

- $D_{KL}(p_{i,j}||q_{i,j})$: The expected utility acquired by transferring packets through channels with maximum utilizations, instead of employing channels with minimum utilizations.
- $D_{KL}(q_{i,j}||p_{i,j})$: The expected utility lost by transferring packets through channels with minimum utilizations, instead of employing channels with maximum utilizations.

Primary Weight Measure at node i is denoted by $\delta_{i,j}$ defined by taking the average of the above measures.

$$\delta_{i,j} = \frac{1}{2}\{D_{KL}(p_{i,j}||q_{i,j}) + D_{KL}(q_{i,j}||p_{i,j})\}. \quad (3.10)$$

The K-L divergence is not symmetric. However, the $\delta_{i,j}$ is symmetric in i, j and indicates the degree of the nonuniform spread of primaries in channels between nodes i and j . When there is no primary user around a particular node, $p_{i,j} = q_{i,j}$ and the $\delta_{i,j} = 0$. However, if primary users are present, channel utilizations follow a continuous distribution so the $D(p_{i,j}||q_{i,j}) > 0$ and consequently $\delta_{i,j} > 0$. For $\delta_{i,j} > 0$, the larger the value of $\delta_{i,j}$, the more the channels that are less occupied by primary users, and thus have priority over the other channels in the vicinity of the node i . When $\delta_{i,j}$ approaches zero, primary users are spread uniformly, and consequently there is no privilege to any transition. Note that when primary users are present, the $\delta_{i,j}$ could be near zero but not exactly equal.

To show how the PWM represents the nature of the spread of primary users on channels around a node, let us look at the following numerical example.

Example 1. Assume there are two nodes 1 and 2, each one has 5 different channels available to its neighbor j . Primary users arrive at each of these channels randomly. The ArgMax probability distribution $p_{1,j}$ indicates the channel that is more likely to stay stable among the other channels. For instance, if channel 3 has been idle the most during N sensing periods, then the $p_{1,j}(3)$ has the maximum value. Now if the primaries are affecting all the channels with the same rate channel 3 might also be the channel that has been idle the least among other channels. Therefore, the difference between $p_{1,j}(3)$ and $q_{1,j}(3)$ is small. As explained above, the PWM measure quantifies this difference. Below, the primaries are spread around node 1 according to normal distribution and around node 2 following a uniform distribution. After evaluating ArgMax and ArgMin probability densities for all channels, we have the following results for each node respectively:

$$node\ 1; \begin{array}{c} \begin{array}{ccccc} ch1 & ch2 & ch3 & ch4 & ch5 \end{array} \\ p_{1,j} \begin{pmatrix} 0.26 & 0.21 & 0.28 & 0.12 & 0.13 \end{pmatrix} \\ q_{1,j} \begin{pmatrix} 0.17 & 0.22 & 0.12 & 0.2 & 0.29 \end{pmatrix} \end{array},$$

$$node\ 2; \begin{array}{c} \begin{array}{ccccc} ch1 & ch2 & ch3 & ch4 & ch5 \end{array} \\ p_{2,j} \begin{pmatrix} 0.13 & 0.18 & 0.25 & 0.19 & 0.25 \end{pmatrix} \\ q_{2,j} \begin{pmatrix} 0.16 & 0.24 & 0.24 & 0.19 & 0.17 \end{pmatrix} \end{array}.$$

The $\delta_{1,j}$ is 0.17 but the $\delta_{2,j}$ is 0.02. As a result, the PWM is substantially lower when the channels are affected uniformly by the arrivals of primary users.

3.4 Summary

In this chapter we proposed two new probability distributions called ArgMax and ArgMin that could be used in probabilistic protocols. The ArgMax probability distribution locates the maximum random variable among a set of random variables, while the ArgMin locates the minimum random variable. Using these two probability distributions, we introduced an interesting measure called primary weight measure, which indicated the frequency and the nature of the distribution of primaries around a particular node. A low value of the primary weight measure metric indicated uniform and frequent primary users interruptions on the channels surrounding a node. With this information MAC and routing decisions are taken more efficiently.

Chapter 4

Stochastic Modeling of Cognitive Radio

Networks and Probabilistic Routing

In this chapter, we focus on modeling a cognitive radio mesh network that is operating in a dynamic environment similar to cities' downtown. More specifically the system is modeled by a semi-Markov process. The ArgMax probability distribution that accurately identifies the most stable available channel corresponding to a neighboring node is used as transition probabilities in the stochastic process of the network. We show that the ArgMax probability distribution is a better candidate than the frequently used OOM probability distribution through developing a Probabilistic Selection Routing Procedure (PSRP) that adopts both probability distributions to guide packets throughout the network. The simulation results suggest that ArgMax enables the routing scheme to adapt to the network dynamic more quickly than the OOM probability distribution. The ArgMax enhances the network throughput and end-to-end delay by over 30% when network load increases. We also present an application of the ArgMin probability distribution by using it to select channels with the lowest duration of availability, and to measure the throughput of the network. Since the CRN is a stochastic system, the minimum spectral capacity is rarely zero. Therefore, the identification of the minimum spectral capacity is useful in the development of a smart channel allocation strategy. We show through simulation that with the help of ArgMin, the worst channel in our setup could be used to transfer time-insensitive data at low rates.

In the next sections we present the definition of a Markov and Semi-Markov process that are adopted in this dissertation to model the dynamics of a CRN. We also discuss the truncated distribution that is used to model the duration of channel availability in CRNs.

4.1 An Overview of Markov and Semi-Markov Process

A Markov chain is a system that moves from one state to the next in such a manner that the future location is independent of the past if the present is known. In Markov chains we do not consider the time it takes to transient from one state to another. Real systems are running on actual time. Markov processes not only take into account the changes of state but also the actual times spent in between [45].

The stochastic process $Y = \{Y_t \in \mathfrak{R}_+\}$ is said to be a Markov process with state space E if for any $t, s \geq 0$ and $j \in E$,

$$P\{Y_{t+s} = j | Y_u; u \leq t\} = P\{Y_{t+s} = j | Y_t\}$$

When the conditional probability mentioned above is independent of $t \geq 0$ for all $i, j \in E$ and $s \geq 0$, the process Y is said to be a time-homogeneous Markov process. For fixed $i, j \in E$, the function $t \rightarrow P_t(i, j)$ is called transition function, where

$$P_t(i, j) = P\{Y_t = j | Y_{t-1} = i\}$$

and the family of matrices $P_t, t \geq 0$, of the transition matrix $P_t(i, j)$ is simply called the transition

matrix of the Markov process Y . The transition functions satisfy the following:

$$P_t(i, j) \geq 0, \quad (4.1)$$

$$\sum_{j \in E} P_t(i, j) = 1, \quad (4.2)$$

$$\sum_{k \in E} P_s(i, k) P_t(k, j) = P_{t+s}(i, j). \quad (4.3)$$

A semi-Markov process is one that, when it enters state i , $i \geq 0$:

1. At the next state, it will enter state j with probability $P_t(i, j)$, $i, j \geq 0$
2. Given that the next state to be entered is j , the time until the transition from i to j occurs has distribution F_{ij} .

From the above dynamics we observed that the operation of the cognitive radio network is similar to a semi-Markov process. It takes a random amount of time for the network traffic to stay in node i before it moves to node j . Let nodes $1, 2, \dots, n$ denote the states of a stochastic process, then the transition of packets could be modeled by a semi-Markov process. Since the spectrum bands that could be used to transfer the packets from node i to node j are random and are chosen based on the specified MAC and routing protocols, the transition probabilities P_{ij} vary for different networks. In this chapter, we use the ArgMax probability distribution to model the P_{ij} s. Based on the above definition, Let $J(t)$ denote the states (nodes) entered at time t . Then $J(t)$ is a semi-Markov process with the state space equal to the number of nodes in the network. Next, we present the definition of the truncated distribution. This distribution is used later to model the density function of the available duration of channels.

4.2 Truncated Distributions

Since the distribution of available usage time of a channel is unknown, we use the concept of a truncated distribution later to model the remaining usage time of available channels. Therefore the definition of a truncated distribution is provided here for the ease of readers. Let Y be a random variable whose distribution function $F(y)$ is not concentrated entirely on $[0, \infty)$. Let $t[Y]$ be a random variable with distribution function

$$\hat{F}(y) = \frac{F(y) - F(0)}{1 - F(0)} = P(Y < y | Y \geq 0), \quad y \geq 0. \quad (4.4)$$

Then $t[Y]$ is called truncated random variable; Zolotarev refers to $t[Y]$ as the cut off of Y at zero [46].

4.3 Cognitive Radio Network Model

The Cognitive Radio Network (CRN) under study has the general architecture of a mesh network, where there exists a gateway node (node G), providing the main access to the internet. The edge routers are connected to the gateway by the intermediate relay routers and the clients who access the edge routers send or receive information at any instant of time.

In a populated urban area, smart phones, PDAs, laptops, radios and TVs operate and use their specific spectrum bands. In a cognitive radio network, a cellular phone acts as a SU sender on an unlicensed 2.4 GHz spectrum band and a SU relay node for transferring a network traffic generated by a personal laptop. A general cognitive radio mesh network architecture is shown in Figure 4.1. In this example, there are 4 spectrum bands available and all the nodes send their traffic to the gateway at the top. As it can be seen, the number of relay nodes and spectrum bands available vary

based on the strength of the radio equipment, inter arrival time of primary users and the number of SUs located in the vicinity of a node. For instance, the senders S1 can access the relay R1 in

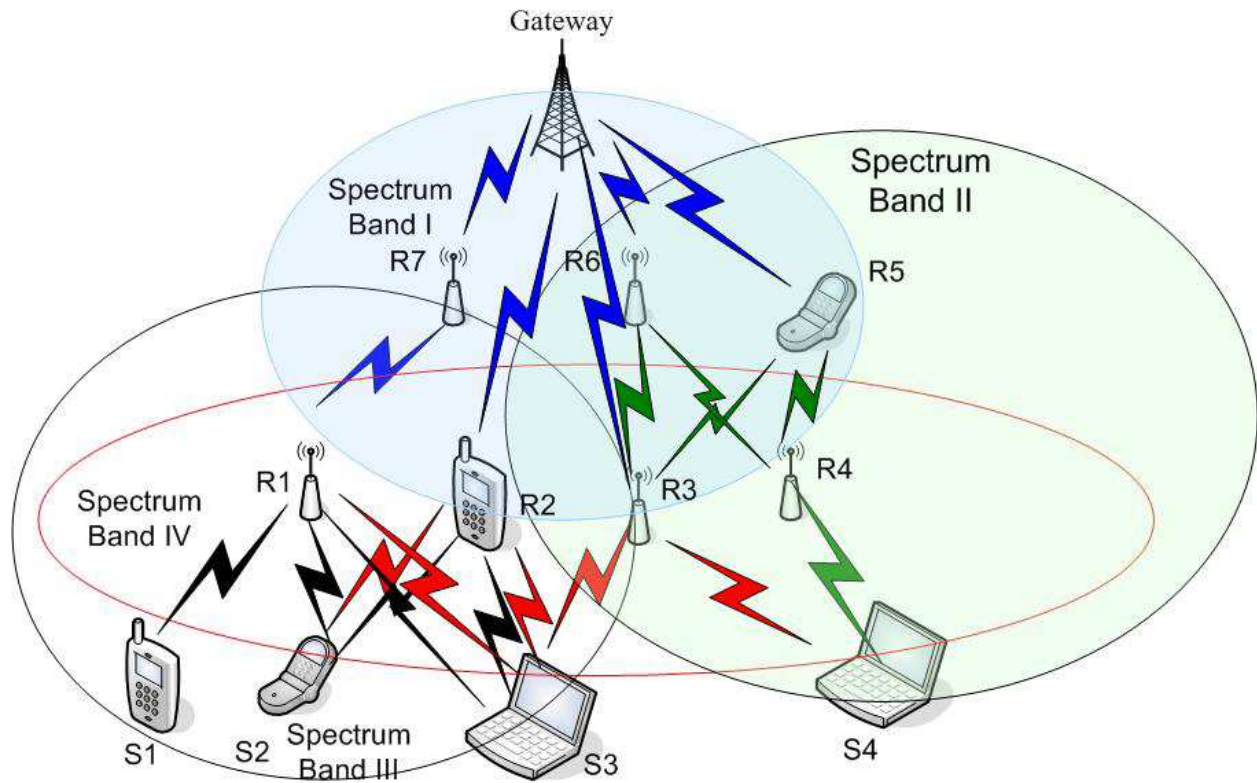


Figure 4.1 A simple mesh cognitive radio network architecture

the domain of spectrum band III but for the cellular phone sender S2, two spectrum bands III and II are available, providing two relays R1 and R2. Since S2 is a secondary user, it should choose a channel from the two spectrum bands that is less interrupted by the arrival of primary users.

When employing CRNs within a city, different sources of uncertainties are present. The behavior of primary users are unpredictable and produce uncertainty in the availability of channel resources. Location discrepancy of primary users causes uncertainty in stability of channels. Furthermore, it is possible that some SUs are affected by many PUs while others are not. Therefore, the transmission bandwidth for each node is variable and is divided among secondary nodes. Moreover, the wireless radio range is affected by the interference and reflection therefore the number of

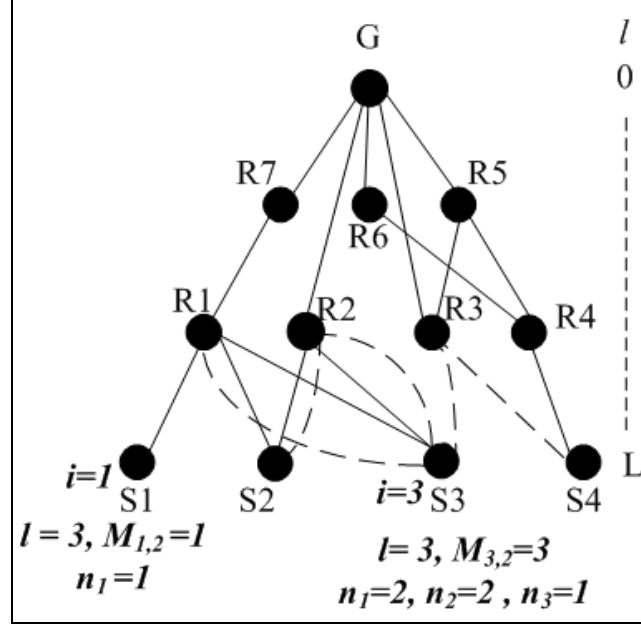


Figure 4.2 The tree graph representation of the simple network architecture. The SU user S1 is the node $i = 1$ in layer $l = 3$ that has $M_{1,2} = 1$ (R1) accessible neighbor, and is connected to it by $n_1 = 1$ channel. The SU user S3 is the node $i = 3$ that has $M_{3,2} = 3$ accessible neighbors (R1, R2, R3), and is connected to R1 by $n_1 = 2$ channels, to R2 by $n_2 = 2$ channels and to R3 by $n_3 = 1$ channel.

accessible relays for a sender is not fixed. As a result, the dynamics of a CRN operating in a city is unpredictable and should be studied under a stochastic framework. In the following sections we present our stochastic modeling of such systems and the PSRP implementation.

4.3.1 Medium Access and Physical Layer Assumptions

We assume the channel is shared with a Non-Contiguous Orthogonal Frequency Division Multiplexing (NC-OFDM) technique. This multi-carrier modulation technique is based on the Orthogonal Frequency Multiplexing (OFDM) technique. By using the NC-OFDM, portions of the target licensed spectrum are occupied by both primary and secondary users. This is achieved by deactivating (i.e. nulling) subcarriers that can potentially interfere with other users. This form of OFDMA fills in the available spectral gaps within the channel's transmission bandwidth partially

occupied by other users while not sacrificing its error robustness [47].

The fluctuation of the wireless channel is modeled by the Rayleigh fading model. According to the study in [48], Rayleigh fading is a useful model in heavily built-up city centers where there is no line-of-sight between the transmitter and receiver.

4.3.2 Spectrum Usage Assumptions

Each spectrum band has a set of channels that are shared by other users with the help of OFDMA/NC multiplexing. All SUs can tune to any combination of licensed channels using a single antenna from different spectrums. Without loss of generality, one PU is associated with one spectrum band (SB). The PU activity is modeled by an OFF/ON process. By the random arrival of PUs the ON period is started.

To model such an agile network, a stochastic framework is considered. Nodes that are located l hop away from the gateway, take a layer index l . Therefore a tree graph topology with L layers is formed. The tree graph topology of our simple example is shown in Figure 6.1b. At a given time t , from the perspective of a secondary user i in layer l , the number of accessible neighbors at each upper layer $l - 1$ is denoted by $M_{i,l-1}(t)$. The number of channels between node i and each of its accessible neighbors j is represented by $N_{ij}(t)$, $j = 1, \dots, M_{i,l-1}(t)$. Therefore, a channel between node i and its upper layer neighbor j is presented by (i, n_j) , $n_j = 1, \dots, N_{ij}(t)$. We summarize the notations in Table 6.1. We suppress the time index t and the layer index l whenever there is no ambiguity.

Since M_i and N_{ij} , $j = 1, \dots, M_i$ are random, elaborating on their distribution is essential. Assume there are a total of M_{l-1}^* nodes in layer $l - 1$. In the initial configuration of the network, nodes identify the layer index of their neighbor nodes by exchanging control messages. We consider a mesh network where the nodes are stationary with long lasting energy. In this case, the hop

Table 4.1 Notations

Symbol	Description.
L	Number of layers.
$M_{i,l-1}(t)$	Number of nodes in layer $l-1$ accessible to a node i in layer l at time t .
$N_{ij}(t)$	Number of channels available between the node i and its neighbor j at time t .
$W_{(i,n_j)}(t)$	Idle period of channels (i, n_j) ; $j = 1, \dots, M_{i,l-1}(t)$, $n_j = 1, \dots, N_{ij}(t)$ at time t .
$X_{(i,n_j)}(t)$	Inter arrival time of PUs on the channels (i, n_j) of a spectrum band at time t .
$Y_{(i,n_j)}(t)$	The amount of time that the PU or other secondary users occupy the channels (i, n_j) at time t .

number would not be dynamic. A node j in layer $l-1$ is considered assessable if it is within node i 's transmission range. For simplicity, we assume that if j is accessible by i , i is also accessible by j . Let d_i be the transmission range of node i , and d_{ij} represent the radial distance of node i from node j at time t . Then the number of accessible neighbors at node i is

$$M_i = \sum_{j=1}^{M_{l-1}^*} I[d_{ij} < d_i], \quad (4.5)$$

where $I(A)$ is the indicator function: $I(A) = 1$, if A is true, and $I(A)=0$, if A is false.

From [47], when the channel is experiencing Rayleigh fading, the total available bandwidth $f_{(i,n_j)}$ of channel (i, n_j) at time t is

$$f_{(i,n_j)} = (1 - \alpha_{(i,n_j)})B_{(i,n_j)}, \quad (4.6)$$

where $B_{(i,n_j)}$ is the total bandwidth (Hz), and $\alpha_{(i,n_j)}$ is the incumbent occupancy of the channel (i, n_j) at time t . The signal-to-noise ratio gain $SNRg_{(i,n_j)}$ of the channel (i, n_j) at time t roughly

indicates the occupancy influence on the channel (the SNR of a shared channel over the SNR of the same channel when it is not shared by other users) and is given by

$$SNRg_{(i,n_j)} = -20 \log_{10}(1 - \alpha_{(i,n_j)}). \quad (4.7)$$

By substituting (4.7) into (4.6), we have

$$f_{(i,n_j)} = B_{(i,n_j)} 10^{(-SNRg_{(i,n_j)}/20)}. \quad (4.8)$$

We represent the inter-arrival time of PUs on the channel (i, n_j) by random variable $X_{(i,n_j)}$ with density function $u_t(x)$ from a SB. The period of occupancy is represented by $Y_{(i,n_j)} = 1/f_{(i,n_j)}$ in seconds with density function $v_t(y)$. Let $W_{(i,n_j)} = X_{(i,n_j)} - Y_{(i,n_j)}$ denote the available usage time of the n th channel between nodes i and j . Then the channel (i, n_j) is available if $W_{(i,n_j)} > 0$. Therefore, the number of channels available between nodes i and j at time t is given by

$$N_{ij} = \sum_{n_j=1}^{N^*} I[W_{(i,n_j)} > 0], \quad (4.9)$$

where N^* is the total number of channels between node i and j from different spectrum bands. We assume the system is in a steady state, and there are stationary distributions on $M_{i,l-1}$ and N_{ij} , not depending on time t . Therefore, the expected number of available nodes is

$$E(M_{i,l-1}) = \sum_{j=1}^{M_{l-1}^*} p_{ij}, \quad (4.10)$$

where $p_{ij} = P[d_{ij} < d_i]$, depends on the strength of the radio signal. Moreover, the expected

number of available channels between nodes i and j is

$$E(N_{ij}) = \sum_{n_j=1}^{N^*} P[W_{(i,n_j)} > 0]. \quad (4.11)$$

Recall that the PU inter-arrival time on channel (i, n_j) is represented by a random variable $X_{(i,n_j)}$ with density function $u_t(x)$, and the occupancy period of other users is shown by a random variable $Y_{(i,n_j)}$. Now, by using the definition of the truncated distribution given in section 4.2 the density function of $\mathfrak{t}[W_{(i,n_j)}]$, the truncation of $W_{(i,n_j)}$ at zero is given by

$$f_{\mathfrak{t}[W]}(w) = \frac{f_{W_t}(w)}{1 - F_W(0)}, \quad w \geq 0 \quad (4.12)$$

where

$$f_{W_t}(x) = \begin{cases} \int_0^\infty v_t(s-x)u_t(s)ds, & x \leq 0, \\ \int_x^\infty v_t(s-x)u_t(s)ds, & x \geq 0. \end{cases}$$

4.4 Probabilistic Routing Approach

In this section we propose the probabilistic routing approach (PSRP) and the usage of ArgMax probability distribution. In the mesh CRN, in which packets move to the upper layers to reach the gateway, transitions form a Markov chain whose states are transient, except for the gateway, which is absorbing. The transition probabilities are not stationary in time, but certain stationary assumptions are made as follows.

- The parameters of the available channel's usage time distributions could be time dependent.

For instance, if the available channel's usage time has Gamma distribution, then the parameters α_t, β_t might be time dependent.

- The accessible states from an upper layer are time dependent random processes, but their distributions are time invariant.
- The transition probabilities are time dependent only because of the time dependency of the available usage time distribution parameters. The PSRP is self updating, in the sense that at the commence of each transition it receives information on the number of spectrums and their time portion of availability. Then, PSRP estimates the parameters of the distributions of the idle period of channels using idle period data that are stored and updated.

Odds-On-Mean (OOM) is an intuitive nonparametric procedure that computes transition probabilities using sample means of the channel idle period data sets. A parametric approach is more informative and gives deep insights into the underlying statistical distributions of the variables governing the system. We should bring to the attention of the reader that PSRP is not a complete routing protocol. It is an uplink routing procedure with the purpose of presenting the strength of the ArgMax over OOM probability distribution. (PSRP will be shown to evolve into a routing protocol in the next chapter.) Following this procedure, node i at layer l constructs its localized Available Resources (AR) matrix at time t after communicating with its neighbors and sensing its environment as follows.

$$AR_l[i; M, N_1, \dots, N_j] = \begin{pmatrix} \tau[W_{1,1}] & \tau[W_{1,1}] & \cdots & \tau[W_{1,1}] \\ \tau[W_{1,2}] & \tau[W_{1,2}] & \cdots & \tau[W_{1,2}] \\ \vdots & \vdots & \ddots & \vdots \\ \tau[W_{1,N_1}] & \tau[W_{1,N_2}] & \cdots & \tau[W_{1,N_M}] \end{pmatrix}.$$

Since the AR matrix is constructed for node i in a specific layer l at time t , these indices are exhibited from our notation when we refer to AR matrix elements. Each column corresponds to a

neighboring node $j = 1, \dots, M$ and N_j is the size of column j that represents the total number of channels available linking node i to node j at time t . The variation of the column index is seen in the N_M index of $\tau[W_{1,N_M}]$ element of the matrix. The random variable $\tau[W_{(i,n_j)}]$ is the available usage time of each channel (i, n_j) at time t . This quantity is related to the available bandwidth as explained in the previous section. Note that the dimensions M, N_1, \dots, N_j are taken to be random as the AR matrix varies for one transition of packets from one layer to another.

The position of the channel (i, n_j^*) with the highest available bandwidth is unknown to node i . Hence, the idea is to define a probability distribution P_S on the set of states $S \equiv S[i; M, N_1, \dots, N_M] = \{(i, n_j), j = 1, \dots, M, n_j = 1, \dots, N_j\}$ such that transition to $S[i, M, N_1, \dots, N_M]$ occurs based on P_S targeting a channel with the highest available usage time for given values of M, N_1, \dots, N_M .

The ArgMax probability distribution locates the index of the maximum element of an array of random variables. Therefore, based on equation 3.7, the transition distribution P_S based on the random available usage time of channels $\tau[W_{(i,n_j)}]$ is

$$P_S(i, n_j^*) = P \left\{ \tau[W_{(i,n_j^*)}] = \max[\tau[W_{(i,n_j)}], (i, n_j) \in S] \right\}.$$

In statistics, whenever the distribution of the estimator is unavailable or is computationally challenging, simulation methods are used to estimate the probability distribution. This method is used by Kulldorff [49]. In network applications, the timely computation of P_S is very important. We use an idea similar to what Kulldorff suggested, and propose a simulation method in the following section to estimate the ArgMax probabilities online.

The OOM probability distribution is the well known probability distribution that is used in most probabilistic routing applications. According to OOM probability distribution in equation

4.13, P_S is

$$P_S(i, n_j^*) = \frac{\mu(i, n_j^*)}{\sum_{j=1}^M \sum_{n_j=1}^{N_m} \mu(i, n_j)}, \quad (4.13)$$

where $\mu(i, n_j^*)$ is the average available bandwidth of the channel (i, n_j^*) between the node i and j . This well known probability distribution is often used since its computation is simple. However, recall that the node in a particular layer wants to identify the path among all the channels from different bands that has the most available bandwidth to transfer the packets to its neighbors in the upper layer. Therefore, OOM does not accurately point to the maximum location.

4.5 Model implementation

This section describes implementation details of the ArgMax and ArgMin distributions and the route selection scheme. We rely on the ability of the software defined radio transceivers embedded in the nodes to detect the number of spectrums available. With the use of NC-OFDMA MAC layer, a SU could select from different channels in a spectrum band and share the channel with other SUs. SUs communicate with each other using a common control channel in the lower portion of the spectrum where the transmission range is higher. The use of the common control channel can improve the reliability of the framework [19]. In the initial configuration of the network, nodes transmit fast messages to each other and try to calculate their distance based on the number of hops from the gateway node. After this step, each node obtains an extra identity index l indicating its layer allocation, which will identify its upper layer neighbors. There is a time period allocated to a node to complete its packet transmission. This time is divided into two parts: decision making time t_d and transmission time t_s . During the decision making time t_d , the following actions are

completed:

1. Node i starts handshaking with each of its upper layer neighbors, and obtains the $SNRg_{(i,n_j)}$ of every channel (i, n_j) connecting its neighbor j . $SNRg_{(i,n_j)}$ is evaluated at the receiver antennas of neighbors.
2. Node i evaluates the available bandwidth, $f_{(i,n_j)}$, of each channel (i, n_j) from their $SNRg_{(i,n_j)}$ based on equation 6.1.
3. The AR matrix is constructed using the values of $f_{(i,n_j)}$. It should be noted that the usage time $\tau[W_{(i,n_j)}]$ of the channel has a one-to-one relationship with the available bandwidth. The more the available bandwidth, the longer the usage time.
 $\tau[W_{(i,n_j)}]$ is used instead of $f_{(i,n_j)}$ in our simulation model to portray a more realistic setting, where our model distributions are gathered by the measurement study in [50]. Notice that the two values (i.e., $\tau[W_{(i,n_j)}]$, $f_{(i,n_j)}$) could be used interchangeably.
4. Node i evaluates the ArgMax or ArgMin probability distributions state space by analyzing its AR matrix as follows:

Simulation Procedure to Estimate ArgMax and Argmin

ArgMax indicates the location of the maximum element and ArgMin indicates the location of the minimum element. Hence in the following steps, whenever the ArgMin needs to be implemented instead of the ArgMax the maximum is replaced by the minimum.

- (a) Node i finds the channel (i, n_j^*) that has the maximum (minimum) $\tau[W_{(i,n_j)}]$ among the AR matrix elements.
- (b) Every time node i tries to route its packets, it looks at its past AR matrices and evaluates the likelihood that the channel (i, n_j^*) has the maximum (minimum) $\tau[W_{(i,n_j)}]$. For

example, consider node i , making its routing decision for the 10th time. If in 4 out of 10 series of stored AR matrices, the channel (i, n_j^*) has the maximum available usage time, then the ArgMax probability of (i, n_j^*) is 4/10. This method of estimating the ArgMax and ArgMin probability distributions is adopted from the method used in [49].

5. Having the probability of each channel, node i applies a Monte Carlo simulation to obtain its routing selection information (i.e. the index of the next hop and the corresponding channel). The Monte Carlo performs a basic selection of candidates based on their probability distributions. We like to emphasize that this simple and non-complex step exists in every probabilistic routing protocol that locates the next node with its transition probability.
6. At this step, node i has the routing information and starts its transmission of packets during the transmission time t_s .

The above steps are summarized in Figure 4.3.

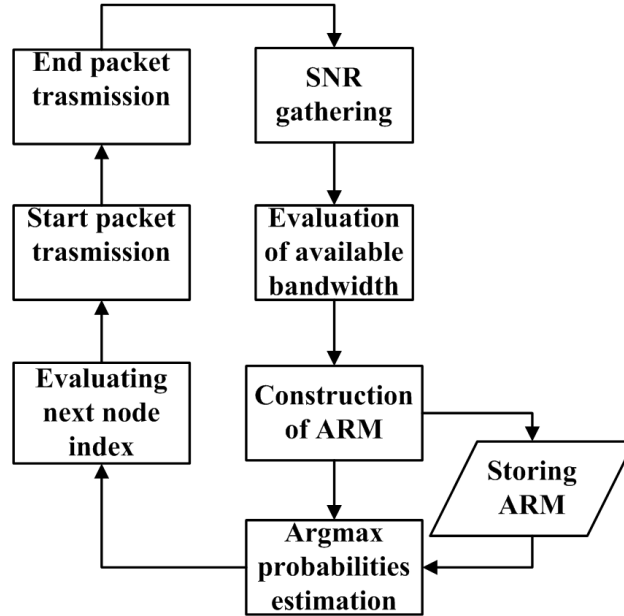


Figure 4.3 The node selection procedure

The run time complexity of the proposed algorithm is $\Theta(n)$, where $n = N^* \times M^*$, N^* and M^* correspond to the maximum row and column size of the AR matrix. The complexity is the same as OOM since the summation over all elements of the AR matrix is needed in estimating OOM as well. We discarded the memory of the node after taking a sample of 100 AR matrices. The OOM finds the maximum average value among the elements of AR matrix. Therefore, to obtain the average value empirically, the sum of the 100 samples of each element should be divided by 100. With 100 samples, we achieve satisfactory estimates for the OOM and ArgMax probability masses. Note that in ArgMax, each time the AR matrix is stored, the index of the maximum variable is evaluated and stored. Overall, the distributed nature of the algorithm makes the maximum number of nodes and channels bounded. Therefore, the amount of memory needed to evaluate the ArgMax is bounded. By using advance processors such as RAW proposed in [51] or multi-core SIMD architecture presented in [52] for software defined radios, the PSRP algorithm is easily implementable on small portable devices such as a cellphone [53].

4.6 Simulation Model

In order to analyze the effect of ArgMax and ArgMin, we simulate a cognitive radio network that operates in a city center. Through our simulation setup we are able to drive actual workloads from the network with varying sizes and dynamical parameters. Thus we have more flexibility over the existing testbeds. In order to simulate a cognitive radio environment in a city center, we arrange the nodes into a tree graph topology shown in Figure 6.1b. An extra identity index l is assigned to each node, indicating the node's layer allocation from other nodes. At time t , the number of accessible nodes $M_{i,l-1}$ from the upper layer vary for each node i depending on the radio signal strength, which is affected by interference, reflection, and radio power. In the initial configuration, each

node i has a random value for its transmission range d_i . In addition, a random value is assigned for the radial distance of node j from node i , d_{ij} . Then $M_{i,l-1}$ is evaluated using equation (4.5). For simplicity, if a node j is accessible from its lower layer node i , then node i is also accessible by j .

4.6.1 Modeling of Inter-arrival Time of Primary Users

The primary user's traffic follows a semi-Markov process with OFF/ON period following the exponential distribution with mean λ . This model is based on the measurement study in [54]. As λ gets larger, the channel is available for a longer period of time to be used by secondary users. We change the value of λ to see the effect of inter-arrival time of primary users on the performance of the network.

4.6.2 Channel Occupancy Modeling

Once the channel is available, it is shared among other users. The usage time of a channel Y is always a positive number. Hence, gamma and lognormal distributions are the two appropriate candidates. We use both of the two distributions to cover a wide range of channel usage patterns. The lognormal distribution is used with different mean μ and standard deviation σ . Based on the measurement study [50] performed on a cellular network in a crowded urban area, the channel occupancy duration is represented by lognormal distribution. Note that the larger the value of μ , the more occupied the channel would be, hence the smaller available usage time $\tau[W_{(i,n_j)}]$ on that channel. Later, to cover traffic patterns other than the one in cellular networks, we substitute the lognormal distribution with the gamma distribution. The two parameters α and β of gamma distribution control the amount of channel usage similar to lognormal distribution parameters.

4.6.3 Modeling of Available Channel Usage Time

The available channel usage times, $\tau[W_{(i,n_j)}]$ s, are generated by truncating $X - Y$ values at zero. The truncated density function is evaluated based on equation 4.12. For each node j there are a total of N_{ij} channels available, which are found based on equation 4.9.

In our simulation setup, we first use the simulation technique described in step 4 of the previous section to evaluate ArgMax probabilities. After assigning the probabilities, a neighboring node from the lower layer is chosen based on a Monte Carlo simulation on channel probabilities. We use these probabilities in PSRP and compare its performance with the case when OOM is used instead of ArgMax. Second, we find ArgMin probability distribution by simply evaluating the minimum element in our simulation instead of the maximum element, and provide the minimal network throughput when the most unstable channels are used. For both scenarios, our simulated model retains and updates the AR matrix values every 100 seconds.

By changing the distributions of primary user arrival patterns and their corresponding parameters, we are able to analyze the performance of ArgMax in different environmental dynamics. We believe our simulation setup mimics real implementations to a good extent because firstly, we selected the distributions in our simulation based on measurement studies on real networks as explained above. Secondly, we tried different distributions as well that were not reported in studies, but are highly probable of occurring in nature such as gamma distribution.

4.7 Results

In this section, we first present the simulation results and compare the performance of ArgMax probability distribution with OOM probability distribution in a probabilistic selection routing algorithm (PSRP). Second we elaborate on the applications of ArgMin by demonstrating network

throughput when channels with minimum duration of availability are used to route packets.

4.7.1 PSRP with ArgMax Probability Distribution

We present the performance of the network in terms of throughput and end-to-end delay under variations of primary user arrival distribution, network load, and network size. We expect to see improvement when the amount of traffic is increased because of the nature of the ArgMax probability distribution. As a result, we evaluate the network with different sending rates to observe different loads on the network.

A network with 75 nodes is selected and the simulation runs for 12 hours. The number of accessible channels for each node changes every 100 seconds. In our simulation model, other SUs behave in diverse manners; a heavy user who uses a large portion of the spectrum, leaving a small portion to be used by others, a light user who consumes a small portion of the spectrum band, and an average user who uses the spectrum band in a moderate fashion. Therefore, three kinds of channels could be available. A lognormal distribution with means 0.8, 0.2, and 0.5, a variance of 0.5, and a gamma distribution with $\alpha = 1.5, 2, 3$ and $\beta = 1$ are used to model this diversity. As explained in previous sections, the truncated distribution of available usage time of channels is estimated using the exponential model for inter-arrival of PUs on channels with $\lambda = 30\text{sec}$ and the lognormal or gamma distribution model of SUs. We have 5 spectrum bands with a minimum bandwidth of 6Mb/sec (which could correspond to FM radio band) and a maximum of 144Mb/sec (similar to a TV channel). Note that a spectrum band can have different numbers of channels depending on its type. The bandwidth of each spectrum is divided equally among its channels. For example, the 144Mb/sec spectrum band has 6 channels, each with a bandwidth of 24 Mb/sec. Overall we have 30 channels with heterogeneous bandwidths in our simulation.

For the routing layer, the total available usage time of each channel is important for selecting

the next node and the access techniques in the MAC layer are responsible for providing the node with an interference free channel from a band. Note that in a cognitive radio the transmission rate varies based on the type of available channel.

Nodes 67 to 78 are sources and they generate packets according to a Poisson process. The packets mean arrival rate follows an exponential distribution between 30ms to 100ms. The packets size is 2000 bytes. We change the sending rate of the packets and observe the performance of the network.

Table 4.2 shows the difference between the average throughput for the two methods when sending rate is changed and lognormal distribution is used to model the channel occupancy of SUs. The PSRP that uses ArgMax in its decision making outperforms the PSRP with OOM. As the sending rate is over 5Mb/sec, ArgMax performs much better than OOM because locating the most stable path with the highest amount of available bandwidth is more crucial when the load increases. In dynamic environments, mislabeling the most stable path would result in a greater amount of packet loss and unwanted delay for the remaining packets. ArgMax chooses the path more precisely and is able to learn the behavior of the network faster. In a very simple analogy, the difference is similar to the difference of selecting a maximum value over an average value from a series of data. The difference is more obvious when the system is in need of timely, accurate decisions. We see the same trend in throughput when gamma distribution is used to model SU behavior in Table 4.3. Therefore we conclude that ArgMax is able to identify the channel with maximum duration of availability regardless of the shape of its corresponding underlying distribution.

We present the overall end-to-end delay of the network with varying sending rates for both OOM and ArgMax in Table 4.4. Our results show that the estimation of the ArgMax probability through our proposed simulation scheme did not increase the delay and even reduced it by 60%.

To investigate the effect of network size, we changed the number of layers l from 6 to 12 while

Table 4.2 Average throughput with 95% confidence interval for different sending rates, $l=12$, 78 nodes

Rate (Mb/s)	OOM Throughput	ArgMax Throughput
2	0.59 ± 0.0104	0.78 ± 0.0033
4	0.88 ± 0.0061	0.96 ± 0.0017
6	0.50 ± 0.0095	0.87 ± 0.0052
8	0.30 ± 0.0071	0.64 ± 0.0122

Table 4.3 Average throughput with 95% confidence interval for different sending rate with Gamma distribution, $l=12$, 78 nodes

Rate (Mb/s)	OOM Throughput	ArgMax Throughput
2	0.873 ± 0.004	0.958 ± 0.0004
4	0.653 ± 0.0018	0.935 ± 0.002
6	0.471 ± 0.0101	0.861 ± 0.006
8	0.366 ± 0.0074	0.751 ± 0.008

Table 4.4 95% confidence interval of average end-to-end delay for different rates

Rate(Mb/sec)	OOM Delay(msec)	ArgMax Delay(msec)
6	383 ± 21	149 ± 4
8	642 ± 34	285 ± 9
10	654 ± 39	397 ± 12

keeping the sending rate constant at a high rate of 8Mb/sec. Table 4.5 shows that network size has little effect on the average throughput of both ArgMax and OOM. This is due to the decentralized nature of the PSRP algorithm. The ArgMax performs better because of its accuracy in locating the path with the maximum available usage time.

Table 4.5 Average throughput with 95% confidence interval for different network size, sending rate is 8Mb/sec

l	OOM Throughput	ArgMax Throughput
6	0.41 ± 0.008	0.66 ± 0.010
8	0.36 ± 0.007	0.65 ± 0.011
10	0.30 ± 0.005	0.64 ± 0.014
12	0.32 ± 0.006	0.6 ± 0.008

Figure 4.4 and Figure 4.5 show the average throughput and the average end-to-end delay when the mean duration of the idle period of PUs λ changes from 15sec to 60sec. As the idle period

of PUs increases, the average throughput increases as well, while the average delay decreases. However, the average throughput and the average delay change gradually when ArgMax is used because the most stable channel is correctly identified, even when the idle period of PUs is small. When OOM is used, the average throughput increases and the average delay decreases abruptly after 30sec because the channels are more stable after this period on average.

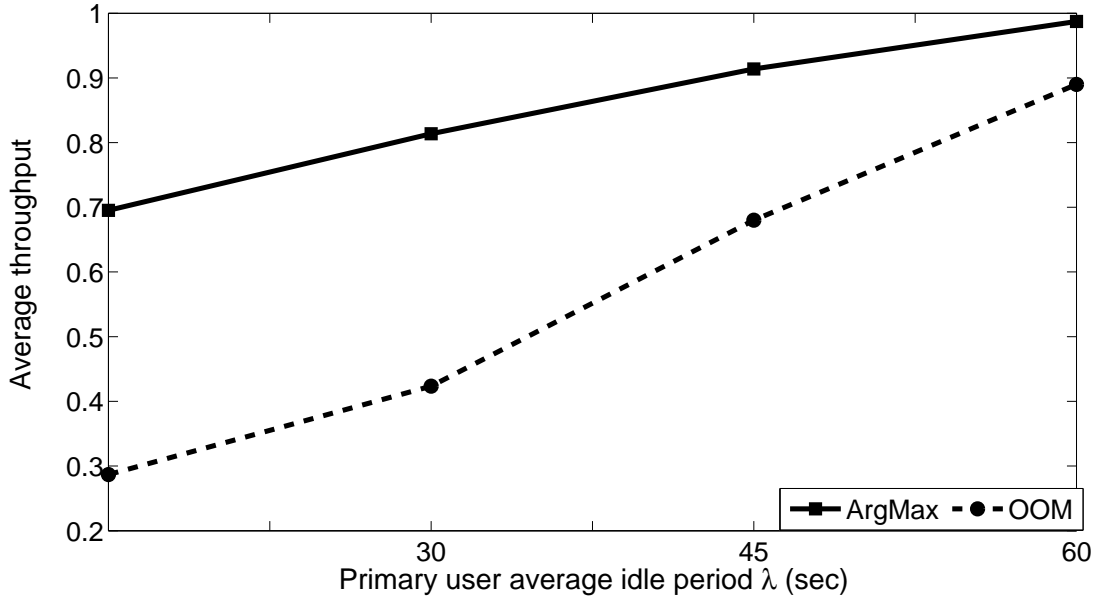


Figure 4.4 Effect of primary users on average throughput for a network with 12 layers and 78 nodes.

Figures 4.6 and 4.7 show the average number of MTUs stored in node queues and the maximum number of dropped packets for each node. Nodes 67 to 78 are not shown in the figures since they are source nodes. The distribution of the number of packets is uniform when PSRP uses ArgMax, distributing the packets fairly over the network nodes by correctly identifying the network dynamics. When PSRP uses OOM, the nodes that are closer to the source fill up fast, but due to the incorrect decision of a stable link, most of the packets are dropped during their trip from source to destination. Therefore the resources of the nodes closer to the gateway are wasted.

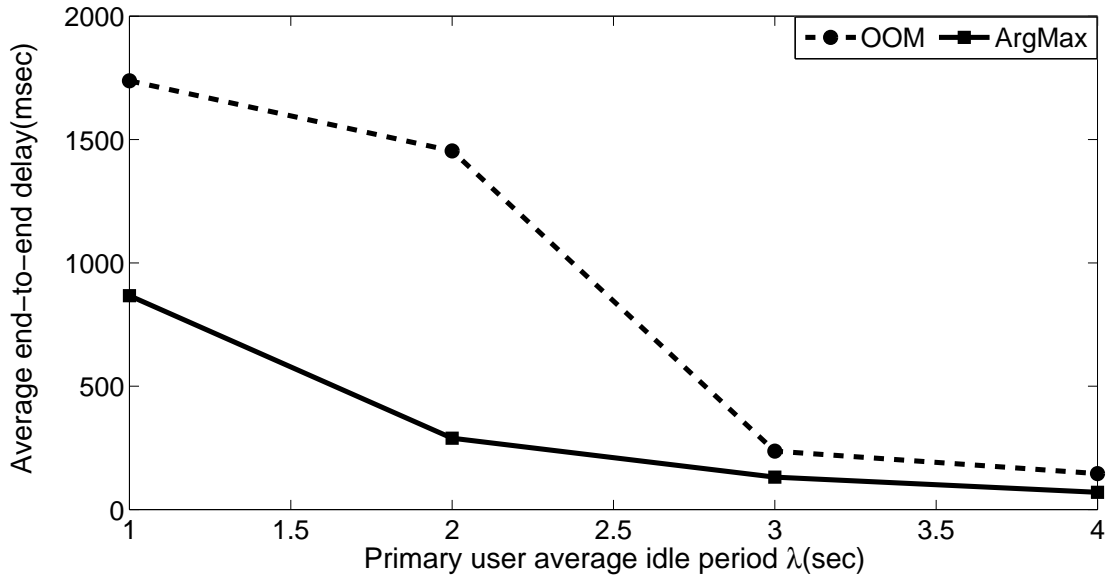


Figure 4.5 Effect of primary users on average delay for a network with 12 layers and 78 nodes.

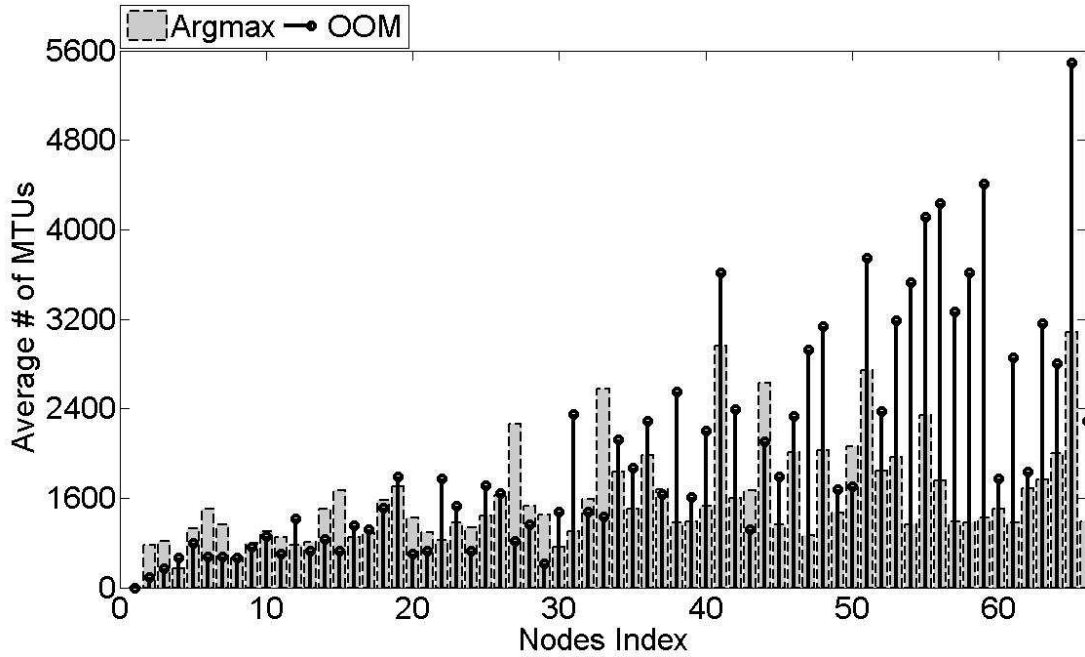


Figure 4.6 Queue Status for a network with 12 layers and 78 nodes.

4.7.2 PSRP with ArgMin Probability Distribution

In this section we evaluate the spectral resources that are available to a node by a channel subject to frequent arrivals of primary users. A node always chooses a channel that is more stable at any

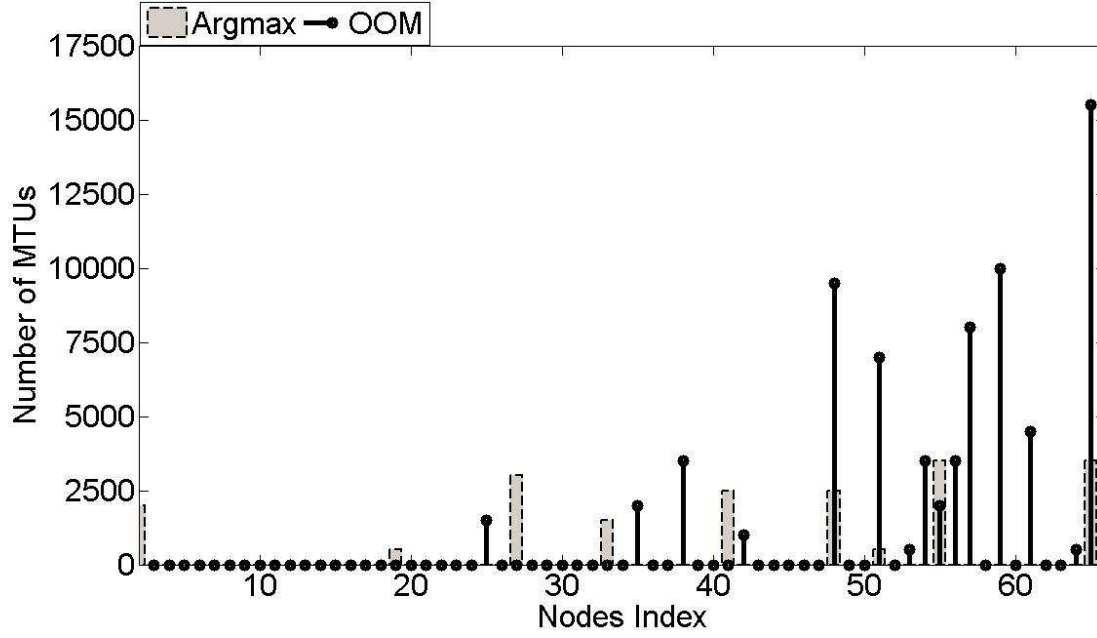


Figure 4.7 Dropped packets status for a network with 12 layers and 78 nodes.

given time and ignores the resources of other channels available. In the stochastic framework of cognitive radio networks, a channel can never be categorized as 100% occupied, but it is given a low priority probabilistically. An interesting observation is to determine the minimal spectral capacity that is offered by our network configuration. In other words, we determine the minimum rate that can be accommodated when the data is sent over the most unstable channels. Figure 4.8 shows the percentage of packets that are successfully received by the gateway when the packets are sent over the worst channels. In the worst case scenario, at 2Mb/sec, 30% of packets reach the destination successfully. Using this information, we change the sending rate from 60Kb/sec to 300Kb/sec, which is only half of 600Kb/sec (i.e. 30% of 2Mb/sec). The results are shown in Figure 4.9. We can see that about 80% of packets are successfully transferred using the channel with the lowest duration of availability at low rates. This result shows that with proper rate scheduling and data classification, cognitive radio networks can truly achieve maximum spectral utilization. With the help of ArgMin probability distribution this minimum capacity is identified and used

for transferring data that do not require high bandwidths or are not time-sensitive. Whenever identification of a minimum random variable is needed, ArgMin comes into play. There are many other scenarios in networking specifically in information theory or coding, where we need such identifications.

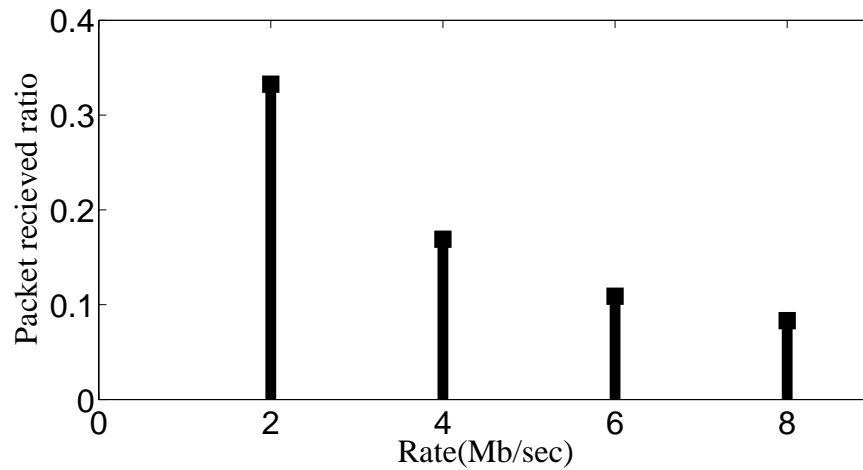


Figure 4.8 Minimum packet delivery ratio of a network with 12 layers and 78 nodes under frequent arrival of primary users.

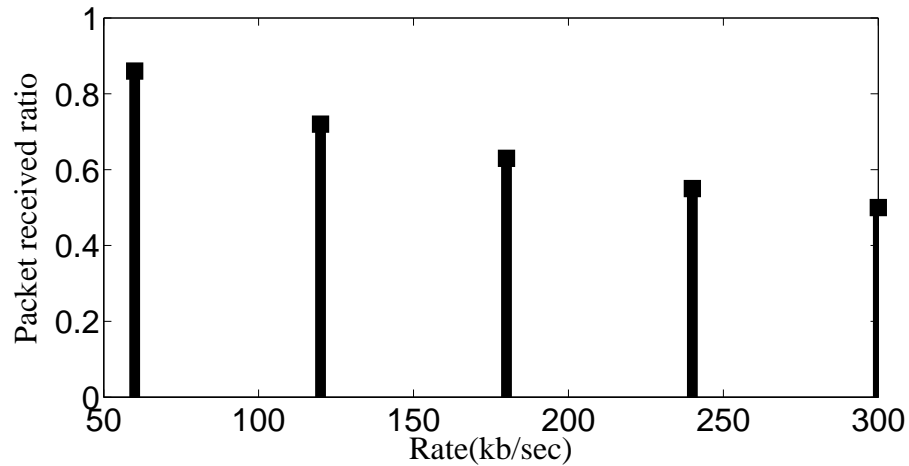


Figure 4.9 Minimum packet delivery ratio of a network with 12 layers and 78 nodes under frequent arrival of primary users at low rates.

4.8 Summary

In this chapter we proposed a decentralized probabilistic routing scheme (PSRP) for a cognitive radio operating in a crowded urban area. PSRP uses ArgMax probability distribution to decide among neighboring nodes with variable band channels. To show the strength of ArgMax over the classical Odds-On-Mean probability distribution, which is used in most probabilistic protocols, PSRP is implemented with both probability distributions. We have shown that the ArgMax is more accurate in modeling and estimating the location of the maximum available band and increases the aggregate throughput significantly. It also decreases the network delay by 60% when the traffic is high. In the next chapter we extend the PSRP into an stochastic protocol.

Chapter 5

Stochastic Routing Protocol

In dynamic cognitive radio mesh networks the variation in spectrum diversity and availability is high due to the presence and the sojourn time of primary users. In this chapter, we use the developed Primary Weight Measure (PWM) metric in Chapter that measures the uniformity of spread of primary users around a particular node and propose a decentralized routing algorithm called *Primary Spread Aware Routing Protocol* (PSARP). The PSARP is an adaptive per-hop routing scheme that, unlike the predecessor schemes, is nondeterministic. The traffic from a source to a destination is modeled by a Markov process, and packets are forwarded hop by hop based on transition probabilities that reflect the next hop spectral availability as well as the entire path quality. The PWM metrics of the nodes are relayed via back-pressure and are used in the construction of transition probabilities. On a cognitive-based NS2 network simulator, we compare the performance of PSARP with two previously developed routing protocols for dynamic environment. We also develop a Cognitive Stochastic Routing (CSR) protocol based on the PSARP stochastic framework that uses backlogged queue capacity instead of PWM. Our results show higher throughput in PSARP and CSR, which indicate the advantage of stochastic-based routing in a dynamic environment. In addition, PSARP with its PWM measure is more successful in choosing the best path due to the correct identification of the primary users' distribution, and performs substantially better than CSR at high rates.

5.1 Stochastic Routing

Stochastic routing is the term given to the process of locating the best route in a stochastic environment using stochastic systems tools. In theory of stochastic systems, the observed system parameters are random and variable. The evolution of the system is governed by transitional probabilities that estimate the possibility of system landing on a next state. System designers create transitional probabilities according to their preference. We observed that the transition of packets from a source to a destination in a cognitive radio network is a stochastic process since the random arrival of primary users on channels make the next state of the system (next hop) in the path indeterministic. Packets may be sent to a next hop but never reach that hop due to the arrival of primary users. Therefore, we develop a stochastic routing scheme that uses the transitional probabilities to find the most stable path. Our protocol is different in nature from all other previous work since it is not deterministic. First, we begin by presenting the protocol operating environment assumptions. Next, the theoretical modeling is presented and finally, the protocol implementation is discussed.

5.1.1 PSARP Operating Environment Assumptions

We consider a mesh network of secondary users in the downtown area of a city, where there are heterogenous primary users with a variety of spectrum availability. Secondary users may choose their particular destinations randomly. We also assume that all users in our system have little to no mobility.

5.1.1.1 Primary User Model

We consider a number of primary users with different transmission range and dynamic behavior. The occupancy pattern of our primary users are random and categorized as follows: A heavy user

that occupies the channel for a longer period of time (e.g., TV band users), a medium user that has an average occupancy period, and a light user has a short period of usage similar to a cellular telephony and data traffic patterns. A number of primary users are randomly deployed throughout the network. Therefore, the secondary channel availability is not consistent. Some secondary users might be affected by more primary users than others. Primary users access their dedicated channel anytime they desire without notifying other secondary users on the channel.

5.1.1.2 Secondary User Model

The secondary users have access to a number of channels from different spectrum bands. The medium access is CSMA. Hence, once a channel is available, other secondary users compete to access the channel and transfer their packets when the channel is sensed idle. If a secondary users senses a primary user transmission, it interrupts its transmission, queues up its packet, and waits for the next channel availability.

5.1.1.3 Medium Access and Physical Medium Model.

The CSMA technique is used by the secondary users to access the physical channel. The CSMA is enhanced with a PU detection mechanism. By the presence of a primary user, the secondary users would not transmit and back-off until primary users have left the channel. Secondary users are equipped with two radio interfaces with omni directional antennas. A control channel is dedicated to the exchange of control packets and is monitored by one interface. Due to the irregular arrival of primary users, a dedicated control channel is necessary for the reliable transfer of control packets. The other interface monitors the data channels. The wireless channel has the Rayleigh fading model. According to [48], Rayleigh fading is appropriate for an urban area, where there is no line of sight between the sender and the receiver.

5.1.2 Theory

As explained in previous chapter, the flow of packets initiated from a sender to a receiver can be modeled by a Markov process with time dependent transition probabilities. The transitions are step wise from one node to another [55]. All the *nodes* of a particular flow form the transient *states* of the Markov chain except the receiver, which is absorbing. Let us consider a secondary network. At a time epoch t , a secondary user sender i chooses any of its neighboring nodes j , $\{j \neq i, j \in M_{i,t}\}$ ($M_{i,t}$: total number of neighboring nodes of i accessible from i at time t) to send its packets to the destination d via channel k , $k = 1, \dots, N_{ij}$ based on the transition probabilities $p_{t[ij;d]}(k)$. The variable N_{ij} represents the total available channels between nodes i and j at time t . The time index t is suppressed from now in our notations whenever there is no ambiguity.

To have a reliable transmission, from a local perspective, the node i at time t looks for a neighboring node j with a reliable link connection. In a global view however, the neighboring node j should be able to forward received packets to the desired destination. In other words, node j should be on a valid path to the destination. Therefore, in any formulation for $p_{t[ij;d]}(k)$, the following two criteria must be addressed.

- Neighbor's forwarding ability
- Neighbor's link quality

5.1.2.1 Neighbor's forwarding ability

To model a node's forwarding ability, a selection probability $g_d(j)$ is assigned to each neighbor node j for a specific ultimate destination d at time t based on its maximum PWM value Δ_j . Probabilistically, the transition must go through the nodes that have maximum PWM meaning they are less affected by the primary users. Therefore, $g_d(j)$ is found based on the odds on PWM

probability distribution as follows.

$$g_d(j) = \frac{\Delta_j}{\sum_{m \in M_{i,d}} \Delta_m}, \quad j \in M_{i,d} \quad (5.1)$$

where $M_{i,d}$ consists of the node i neighbor nodes that could be chosen for the ultimate destination d at time t .

$$\Delta_j = \max\{\delta_{j,m}, \quad m \in M_{j,d}\} \quad (5.2)$$

The set $M_{i,d}$ is identified in the initial setup phase of the PSARP protocol. As explained in section 3.3, when $\Delta_j = 0$, there are no primary users around the node j . Therefore, $g_d(j) = 1$.

5.1.2.2 Link reliability

A link between node i and node j is stable if it is less interrupted by the primary users. When a primary user is absent, the channel is used by other secondary users. Therefore, a link reliability metric should also capture other secondary users traffic load on the channel. We use the ArgMax probability distribution to characterize the channel that has the maximum utility among the set of all available channels. Therefore, the probability that channel n at node i has the maximum utility is $P_{ij}(n)$, evaluated using equation (3.7).

5.1.2.3 System Transitional Probabilities

Let us summarize the probabilistic dynamics of transitions. A node i seeks an accessible node with maximum PWM through a link with maximum utilization at a given epoch. The system has stochastic dynamics; consequently, the desirable nodes and links are subject to change. The transition has two stages: the selection of the desirable neighboring node for the ultimate destination d ,

and the selection of the desirable link. The tree diagram with root i and branches $[i \rightarrow j, j \rightarrow k_j]$, $j = 1, \dots, M_{i,d}, k_j = 1, \dots, N_{ij}$, shown in Figure 5.1, depicts the transitions from i to j through channel k . Thus, the transition probability from i to j through the channel k at time t is

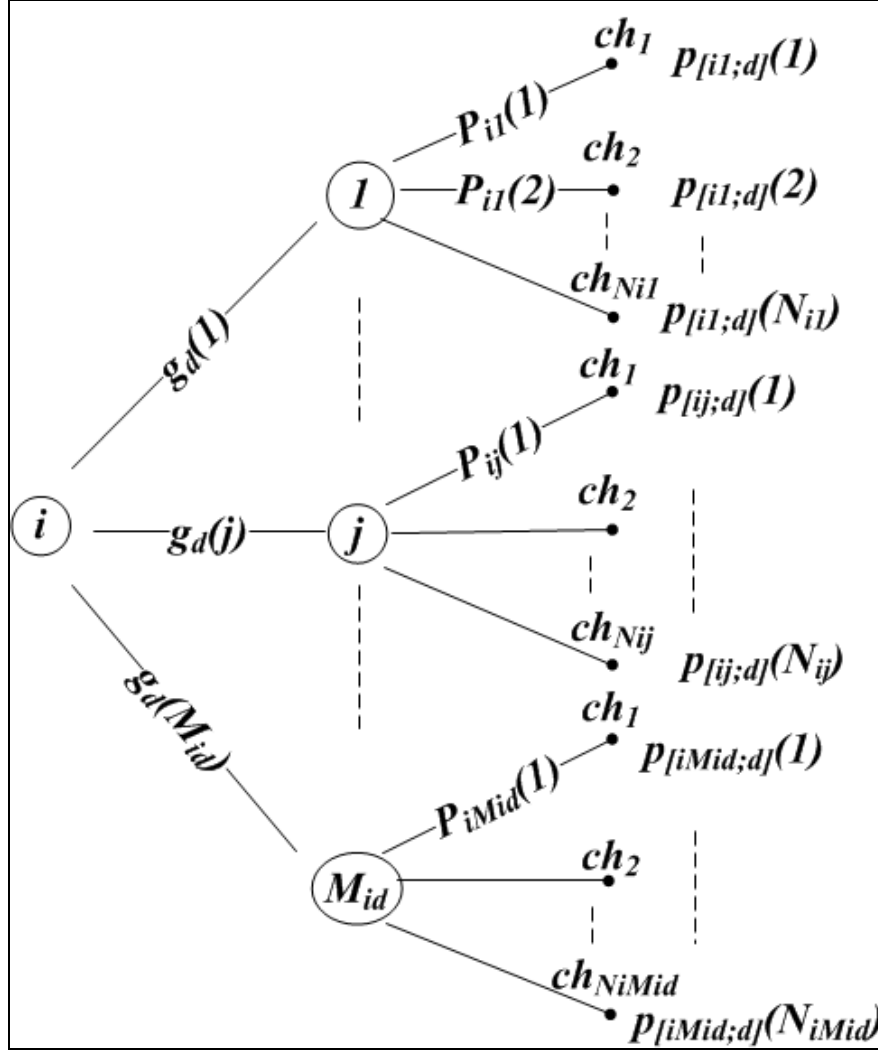


Figure 5.1 Transition probabilities tree diagram

$$p_{[ij;d]}^{(k)} = g_d(j)P_{ij}^{(k)}. \quad (5.3)$$

Therefore the transition is from i to any of the states in $\{(j, k) : j = 1, \dots, M_{i,d}, k_j = 1, \dots, N_{ij}\}$ The following matrix governs the transition probabilities.

$$T_{id} = \begin{pmatrix} p_{[i1;d]}^{(1)} & p_{[i2;d]}^{(1)} & \cdots & p_{[iM_{i,d};d]}^{(1)} \\ p_{[i1;d]}^{(2)} & p_{[i2;d]}^{(2)} & \cdots & p_{[iM_{i,d};d]}^{(2)} \\ \vdots & \vdots & \ddots & \vdots \\ p_{[i1;d]}^{(N_{i1})} & p_{[i2;d]}^{(N_{i2})} & \cdots & p_{[iM_{i,d};d]}^{(N_{iM_{i,d}})} \end{pmatrix}, \quad (5.4)$$

The number of columns of T_{id} , $M_{i,d}$, is the number of neighbors available to node i leading to destination d at time t , and the number of rows, N_{ij} , is the number of channels available between node i and its neighbor j at time t .

Clearly, $\sum_{jk}^{N_{i,j} M_{i,d}} P_{ij,d}[t; ch_k] = 1$. We see this is satisfied since the elements of the transition matrix T_{id} are the ending branches of the conditional tree diagram in Figure 5.1. In the next subsection, we present the framework and forwarding mechanism based on the transition matrix T_{id} of PSARP.

5.1.3 PSARP Implementation

In this section we layout the implementation of the stochastic protocol. First, we list different routing components that are used to make the protocol reliable and sustainable in actual implementation. Second, we explain how these components are constructed. Finally, we explain the adaptive per-hop forwarding procedure by following packets from a source to a destination. We categorized the routing components into:

1. Tables
2. Control messages

3. Transition probabilities

5.1.3.1 PSARP Tables

Two tables are held and maintained at each CR nodes.

- Neighbor table

Similar to AODV based protocols [31], CODV [32], OSDRP [33], each node holds a table to store some attributes of its neighbors. These attributes will eliminate the count to infinity and the discontinuity problems that are usually present in a decentralized decision making protocols. A neighbor table entry corresponding to a neighbor j is shown in Table 5.1.

Table 5.1 An entry of the neighbor Table

Neighbor Id (j)
Destination Id (d)
Number of hops
Authorization index (connectivity attribute)
Time to live (Expiration time for this node)
Max PWM, Δ_j
Reception channel k^* .

The channel utilization effect is captured in evaluating the channel k^* that has the maximum utility around neighbor j by using equation (3.7).

- Forwarding table

The entries in the forwarding table construct the sets of candidates among the neighbors that are suitable to receive packets for a specific destination. See Table 5.2. Each node uses the forwarding table information to construct its transitional probabilities. This process is explained in detail in the following subsections. Active neighbors are those with a

lower number of hops and a valid authorization index; this information is obtained from the neighbor table. Note that the forwarding table also exists in the other routing protocols.

Table 5.2 An entry of the forwarding Table

Destination
List of authorized neighbors
$p_{[ij;d]}^{(k)}$ transition probabilities for all authorized neighbors

5.1.3.2 Control Messages

In order to update the entries of the neighbor table and forwarding table according to the system dynamics, neighbors exchange two types of control messages.

- HELLO Packet

Similar to decentralized protocols, HELLO packets are responsible to update the neighbor and forwarding table of each node. A HELLO packet carries the destination of the next packet waiting to be transmitted. The HELLO packet is generated when a node does not have an entry for a particular destination or when the transition probability update period is reached. HELLO packets are broadcast to neighbors on the common control channel with the following information:

- Destination
- Number of hops
- Max PWM, Δ_j
- Received channel ID

Upon receiving the HELLO packet, the node updates the corresponding information in its

Neighbor table. In order to avoid HELLO packet collisions, nodes send HELLO packets in random time slots.

- Destination Acknowledgment DACK Packet

In order to avoid isolated nodes, the neighbors are authorized for a specific destination. To set the authorization index in the neighbor table, when destination receives a message, it will generate the DACK message. Instead of acknowledging each path, which may introduce overhead for long packet headers, we authorize each neighbor via back-pressure. See Figure 5.2. Node 1 wants to send to node 4. Once node 4 receives a packet, node 4 authorizes 2 and 3, letting them know that they can reach node 4. Then, nodes 2 and 3 authorize 1, letting node 1 know that it can reach 4 through 2, 3. The DACK is sent locally. Once a

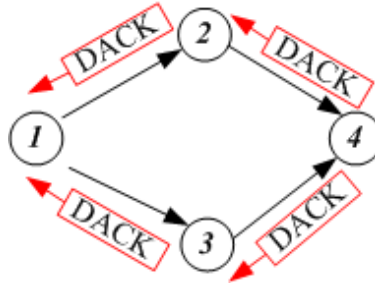


Figure 5.2 Simple topology, node 4 is the destination, generating DACK messages.

node is authorized, no DACK message will be sent to it. We also authorize all paths with a minimum number of hops to the destination to skip long paths. The DACK messages are only sent in the initial set up. We consider a mesh network where the nodes are stationary with long lasting energy. Therefore, the hop number would not be dynamic. Note that the dynamics of channel availability and node occupancy are included in the T_{id} matrix. Hence, contrary to DSR, DSDV, AODV, and other reactive and proactive protocols, we do not need to repeat this process during network operation.

5.1.3.3 Transition Probabilities

As mentioned earlier, the next node is found based on the transition probability associated to it. In order to find each entry of the transition matrix $T_{i,d}$, $P_{ij}(k)$ is calculated by both nodes i and j , and the $g_d(j)$ is evaluated by node i based on the values of Δ_j that are stored in its Neighbor table.

- Evaluation of Channel Reliability Probabilities

Each node i is aware of its surrounding and gathers the number of times that a channel k is sensed idle ($u_{ij}[k]$, the channel utilization parameter for each channel k). It constructs the following vector for a pre-specified observation period:

$$R_i(t) = [u_{ij}[1] \dots u_{ij}[k]].$$

Therefore, the node has many realization of vector $R_i(t)$ after t sensing periods. The ArgMax and ArgMin probability distributions corresponding to the channel utilizations are evaluated based on simplified simulation method presented in Algorithm 1. The variable T_{max} corresponds to the maximum number of observations. The variables Max_k and Min_k represent the number of times that channel k has the maximum and minimum utilization respectively.

- Evaluation of Forwarding Ability Probabilities

The Δ_j metric of the neighboring node j informs the sender i of the distribution of primary users around its neighbor j . Each node j calculates its Δ_j according to equation (5.2) at each time t that a Hello-reply packet is sent. Based on the Δ_j obtained from all the neighbors, $p_{[ij;d]}$ is calculated for each neighboring node j based on equation (5.1).

Algorithm 1 ArgMax and ArgMin probabilities calculation procedure

```
for  $t = 1$  to  $T_{max}$  do
  in  $R_i(t)$ 
  if channel  $k$  has the maximum  $u_{ij}$  then
     $Max_k = Max_k + 1$ 
  end if
  if channel  $k$  has the minimum  $u_{ij}$  then
     $Min_k = Min_k + 1$ 
  end if
end for
 $P_{ij}(k) = Max_k / T_{max}$ 
 $Q_{ij}(k) = Min_k / T_{max}$ 
```

5.1.3.4 PSARP Forwarding Mechanism

The procedure of forwarding packets from a source to a destination is presented here. In the initial setup the neighbor and forwarding tables need to be constructed. Hence, to identify the authorized neighbors, source nodes broadcast the data packets destined for a particular destination. By simple flooding, the packets are delivered to the destination. The destination generates the DACK messages and the nodes that are authorized by receiving the DACK packet from the destination, will authorize their neighbors as explained in the construction of control messages above. The DACK messages are propagated back to the source so that the source node can update the forwarding table. After this initial setup the forwarding mechanism is as follows:

- The source node i ;
 1. Checks the neighbor table to see if the destination d is in the neighbor table. If not, broadcasts the message (waits for DACK messages to arrive).
 2. Sends the HELLO packets and collects the HELLO packets from its neighbors. Hence, the forwarding and neighbor table elements are updated.
 3. Computes $p_{[ij;d]}(k)$ for each neighbor based on equation (5.3).

4. Sends number of packets with the same destination to neighbor j proportional to the value of $p_{[ij;d]}^{(k)}$. Therefore, the neighbor j that has the highest value of $p_{[ij;d]}^{(k)}$ associated to it, is more often the next hop.
- The intermediate node j upon receiving a message, checks the destination of the message and
 1. Checks the neighbor table to see if the destination d is in the neighbor table. If not, broadcasts the message (waits for DACK messages to arrive).
 2. Looks at the forwarding table, if there is a neighbor h for the destination d , gets the transition probabilities $p_{[jh;d]}^{(k)}$ from the table.
 3. Forwards the number of packets destined to d to neighbor h proportional to the value of $p_{[jh;d]}^{(k)}$.
 - The destination node d receives the packets and looks up the previous hop from the message header and checks if it is included in the list of the authorized previous hops. If not, the destination gathers a list of the unauthorized previous hops and insert them in the DACK message. The DACK message is then broadcasted. Therefore, all the unauthorized previous hops are authorized with one DACK message.

5.2 Additional Features

Here, we elaborate on some features embedded in PSARP that may be used in other stochastic routing protocols.

5.2.1 Update Period

Note that the $p_{[ij;d]}(k)$ is highly dependent on how fast $P_{ij}(k)$ and $g_d(j)$ are updated. Currently, the update period is around one second. During this period, we can have 100 samples of R_i matrices to estimate $\hat{P}_{ij}(k)$ and $\hat{g}_d(j)$. From the law of the iterated algorithm proposed by Kolmogorov in [56], the upper and lower bound on the rate of convergence of the estimator of a distribution to its true value are as follows:

$$\limsup_{n \rightarrow \infty} \frac{\sqrt{n} \|\hat{P}_n - P\|}{\sqrt{2 \ln \ln n}} \leq 1/2$$

$$\liminf_{n \rightarrow \infty} \sqrt{2n \ln \ln n} \|\hat{P}_n - P\| = \pi/2$$

where n is the number of samples. From the above we can find the upper bound on the error of the estimator based on n , for large n

$$\|\hat{P}_n - P\| < \frac{\sqrt{\ln \ln n}}{\sqrt{2n}} \quad (5.5)$$

We can see that by selecting $n = 100$, the error is about 0.15; and as n increases, the rate of convergence will go exponentially to zero. By selecting $n = 200$, the error is 0.004. Therefore, by having our update period around one second, or in other words by collecting 100 to 200 samples, we have a very good estimate for the ArgMax and OOM distributions corresponding to $P_{ij}(k)$ and $g_d(j)$ respectively.

5.2.2 Channel Selection Mechanism

The process of handshaking with neighbors in CRNs is challenging. A neighboring node that chooses to change its channel due to the presence of a primary user should notify its neighbors of

its decision in a timely manner. Nodes choose their sending channel based on their local sensing measurement. For instance, suppose node 1 is choosing channel 1 because the $P_{12}(1)$ is maximum, while node 2 is selecting channel 2 because based on its sensing measurement $P_{2j}(2)$ is maximum, where node j is a neighbor of node 2. Therefore node 1 should check which channel node 2 is on before sending its packet on its decided channel. We have the following mechanism in place to reduce packet loss for such a scenario. This mechanism will also reduce handshaking overhead.

- 1) Each node chooses its receiving channel according to the values of the ArgMax probability distribution that locates the channel with the maximum idle frequency in the set of available channels. The channel ID is sent to neighbors via HELLO packets and saved in the neighbor table.
- 2) When node i wants to send its packets, the next hop j is selected based on the transition probability $p_{[ij;d]}^{(k)}$ in equation (5.3). Then, node i switches to the receiving channel of node j for sending. If the receiving channel of node j is occupied on the side of node i , the next hop is reselected.
- 3) After sending, node i switches back to its own best receiving channel.

We can see that this mechanism forces the node to choose a link that is reliable at the both sender and receiver side.

5.3 Evaluation

We study the effectiveness of PSARP in a dynamic environment through simulation. The current version of NS2 computer simulator has the traditional MAC layer that is suitable for evaluating protocols designed for wireless networks. However, a cognitive radio network has its own enhanced MAC layer. In order to test the routing layer, we designed the cognitive MAC layer. We started

by using the open source Cognitive Radio Cognitive Network simulator (CRCN) [57]. Although a primary user is defined in CRCN, the MAC layer would not interrupt its transmission when sensing primary users' activities. Furthermore, the primary users' traffic does not have priority to secondary users' traffic. Hence, the CRCN MAC layer is modified substantially to incorporate these realistic scenarios.

We focus on a *dynamic* environment. The primary transmitters and receivers locations are unknown and their transmission duration is unpredictable. Therefore, we compare the protocol with the Local Coordination Based Routing and spectrum assignment (LCBR) [58], and OSDRP [33]. The LCBR is an AODV based protocol that uses the summation of frequency switching and back off delay at a node on top of the number of hops as its routing metric. The protocol also identifies traversing flows at each node and calculates the active frequency bands taken, which are used for multi-flow multi-frequency scheduling. As mentioned in the related work, many other schemes that are designed for the dynamic environment adopt the same approach. The OSDRP estimates the route lifetime based on the channel availability, as well as channel switching and queuing delays, and adjusts the time of a flow according to the route lifetime. In addition, it controls the transmission power and selects the nearest forwarding SUs to the SU destination node to support QoS.

Further more, to show that the PWM measure truly has an advantage to show the distribution of primaries around a node, we also compare the PSARP with the Cognitive Stochastic Routing (CSR) protocol that we developed. CSR has the same stochastic dynamics as PSARP but uses the backlogged queue capacities as an indication of next node's reliability instead of PWM. The results show that the stochastic approach we proposed is indeed successful in coping with the uncertainties in dynamic environment in both protocols. However, the PSARP performs better because the PWM measure enables it to recognize unstable routes more accurately.

We used different scenarios. In the first scenario a network with 30 nodes with 4 primary users in a 1000×1000 sqm area is considered. The secondary users are spread randomly throughout the plane. The radio range is 250m and a channel is dedicated to the control channel with the bandwidth of 250kb/sec. Three other channels are available, each with the bandwidth of 2Mb/sec. The secondary nodes are able to switch to another channel when their transmission is interrupted or the channel is occupied. This scenario is similar to the test configuration of the OSDRP protocol.

5.3.1 Primary Users Traffic Patterns

The distribution of the inter-arrival time of primary users is exponential with a mean of 3.0. As a result, the primary user's traffic follows a Semi-Markov process with an OFF/ON period following the exponential distribution. This illustrates the model presented in the measurement study [54] of the behavior of primary users. Note that under the uniform distribution, small, mid-size, and large values assume the same frequencies. In other words, the frequencies that a primary user who is on for a short time and a primary user who is using the channel for a longer period are the same. Therefore, the uniform distribution is not a legitimate distribution for the sojourn time of a primary user. The exponential distribution ideally explains the sojourn time distribution in which the frequency of a primary users whose sojourn time exceeds a threshold τ decreases exponentially.

To evaluate PSARP under different primary user patterns, we changed both the distributions and their corresponding mean of the idle period of primary users and kept all the parameters of scenario 1 constant. The average throughput of the protocols is shown in Table 5.3. With the exponential pattern, all four protocols gain higher throughput. This was expected, since the shape of the distribution is skewed to the right. The average idle period will be higher than the uniform distribution. PSARP and CSR maintain throughput even though the inter-arrival time of primary users is changing from 3 to 30 seconds. When the inter-arrival time of primary users is 3 seconds,

Table 5.3 Average throughput (bytes/sec), (30-node network) with different primary users traffic patterns

Average Idle Period (sec)	OSDRP	LCBR	CSR	PSARP
Exponential (mean 3 sec)	2.30E4	3.49E4	5.20E4	5.5E4
Exponential (mean 30 sec)	4.40E4	4.70E4	4.80E4	5.10E4
Uniform (mean 3 sec)	2.20E4	3.3E04	4.50E4	4.80E4
Uniform (mean 30 sec)	3.91E4	4.40E4	4.51E	4.83E4

the protocols should quickly adapt to the changes in the network dynamics. The PSARP adapts to the primaries' change of behavior. Its good performance is also an indication that the transition probabilities are estimated in a timely manner to cope with the uncertainties. The OSDRP and LCBR are not successful in capturing the randomness effect because of their deterministic framework and frequent calling of route recovery mechanisms. However, as the idle periods increase, meaning the channels are less interrupted by the primary users, the throughput of both protocols improves and approaches that of the CSR and PSRP. This shows that stochastic modeling works better than deterministic modeling when the environment is dynamic.

5.3.2 Effect of Network Load

We were also interested in measuring the performance of protocols under different loading conditions. We change the sending rate from 81kb/sec to 1638kb/sec in the first scenario. We use the exponential distribution with the mean of 3 for the inter-arrival time for the primary users. We used 15 different random scenarios with the same configuration as the first scenario, the results shown in Figure 5.3 and Figure 5.4 are the average of the throughput and end-to-end delay from all the 15 random scenarios. There is a peak around a 409kb/sec rate in all four protocols. This was expected since there are 8 CBR connections, meaning 8 sources are sending packets with 409Kb/sec. The channel's bandwidth is 2Mb/sec. If the packets are distributed fairly across all three channels, the network generates high throughput around this rate. However, if the availabil-

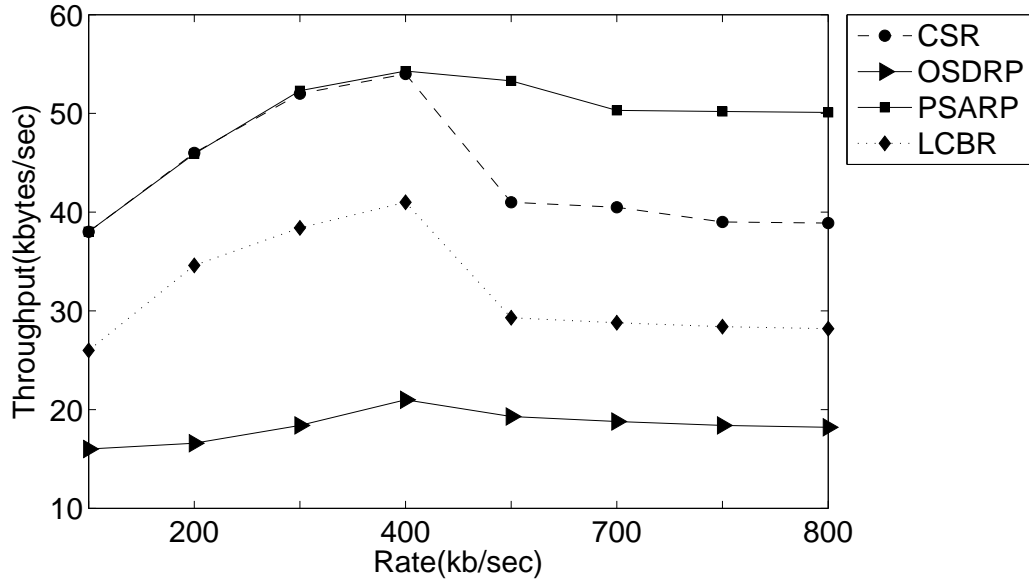


Figure 5.3 Average throughput under different loading conditions, 30-nodes network.

ity of a channel is not determined accurately and packets are sent through an unreliable channel or if the route is not updated on time, a bottleneck is generated. When the sending rate is higher than 409kb/sec, the overall sending rate is more than the channel capacity. As a result, queues fill up quickly. The power of PSARP and CSR are in their stochastic nature. Both protocols benefit from the uncertainty of the network parameters. Hence, while OSDRP and LCBR try to find a new route by unexpected arrival of a primary users, PSARP and CSR stochastic framework have already predicted primary users arrival and chosen an appropriate node for forwarding the packets to. PSARP and CSR learn and adapt to the primary users' behavior more quickly. In OSDRP and LCBR, when a link disappears, the corresponding node is removed from the routing table and the new route discovery mechanism is initiated. Hence, the network operates with less nodes and does not reach its optimal performance and generates less throughput. The LCBR performs better than OSDRP due to its spectrum assignment mechanism that helps a node to forward packets with less channel switching. We can see at higher rates that the network saturates and throughput drops. The

sharp decrease in CSR is due to the decrease in queue capacity variation. Hence CSR selection is blind to the behavioral pattern of primary users located one hop away from the intermediate neighbors at high rates. PSARP on the other hand, uses the PWM measure and is able to identify the correct path. In Figure 5.4, we represent the end-to-end delay comparison. Since the environment is highly dynamic, OSDRP does deliver a substantial amount of packets compared to PSARP and CSR, which adds to end-to-end delay. PSARP and CSR are using ArgMax probability distribution in locating the channel with the maximum utilization. The strength of ArgMax probability distribution is in its accurate identification of the maximum random variable among a set of random variables. Therefore, the channel that is chosen has a higher probability to stay stable and provide stable transmission. Therefore, packets are rarely buffered in the network. This further enhances the performance of the PSARP and CSR and minimizes its end to end delay. Since PSARP chooses the more stable path, its end to end delay is better than CSR. At the rate of 409kb/sec, CSR and PSARP delay are the lowest and the throughput is at its peak value.

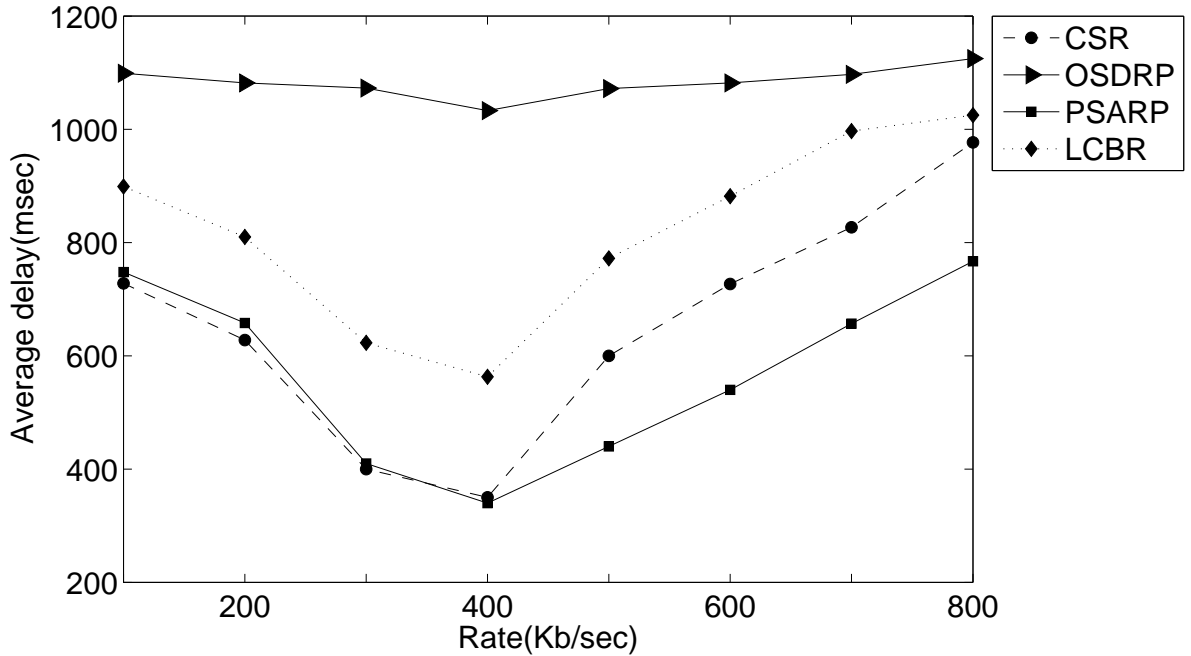


Figure 5.4 Average end-to-end delay under different loading conditions, 30-nodes network.

5.3.3 Large Network

In the second scenario, we use a network with 70 nodes. The sending rate is $409kb/sec$. The number of primary users are 15, and they choose different channels from the three available channels. There are 10 CBR connections and sources are distributed randomly in a 1500×1500 sqm field. Since primary users' inter-arrival time is random, learning their behavior and selecting the route adaptively substantially improves the performance of the network. Table 5.4, shows the simulation results for different distribution for the inter-arrival time of primary users. We can see that OSDRP fails substantially to deliver packets due to the large instability of links and nodes. However, as the idle period of the primaries increases and the network operational environment is closer to a semi-dynamic environment, OSDRP and LCBR throughput increases. On the other hand, PSARP is still successful in maintaining throughput within a range and adapts to the uncertainties. Since PSARP and CSR are stochastic in nature, their throughput degrades as the environment tends to be more static. The reason is that a node in these protocols selects the next hop and the receiving channel probabilistically. It does not stay on a specific best channel or rely on a specific best next hop. Nevertheless, PSARP has a higher throughput than CSR because the PWM measure captures the distribution of primaries more accurately than the queue average backlogged capacity. When the environment is semi-dynamic, PSARP performs slightly better than OSDRP and LCBR because it distributes the packets fairly among the nodes based on its selection probabilities.

Table 5.4 Average throughput (bytes/sec), (70-node network) with different primary users traffic patterns

Average Idle Period	DSODV	LCBR	CSR	PSARP
Exponential (mean 3 sec)	1.35E4	2.01E4	3.8E4	3.95E4
Exponential (mean 30 sec)	3.91E4	4.1E4	3.84E	4.10E4
Uniform (mean 3 sec)	1.20E4	1.9E4	3.75E4	3.91E4
Uniform (mean 30 sec)	3.70E4	3.8E4	3.71E4	4.02E4

We also test the performance of PSARP under different loading conditions in the large network.

Figure 5.5 present the average throughput. Although the network size has increased, the PSARP is still successful in maintaining the throughput. The queues have more variations in their capacities, when there are more nodes in the network. Therefore, CSR throughput has less variation and degrades slower compared to the scenario 1. The OSDRP and LCBR are showing the same trends as scenario 1. Maintaining throughput is very useful in applications that require a guarantee of delivery within a certain user defined quality of service range. In the future, it will be interesting to evaluate the lower and upper bound of the PSARP delivery range. Evaluation of the delivery range is useful to control the applications' sending rate in order to have a guaranteed delivery in dynamic CRNs. Finally we present the comparison of the relative overhead frequency of the pro-

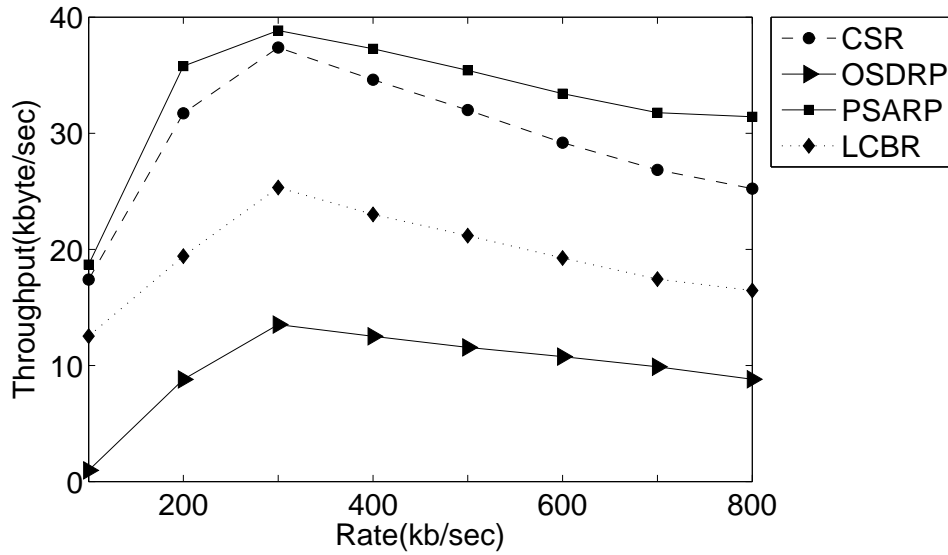


Figure 5.5 Average throughput under different loading condition, 70-nodes network.

ocols over the first four hours of the large network operation in Figure 5.6. The relative overhead frequency is the ratio of the number of overhead packets of each protocol over the total number of overhead packets collected from all four protocols over that particular hour. The relative overhead frequency of PSARP and CSR is larger in the first hour of operation due to the transmission of DACK messages. Recall that the DACK messages are needed in the initial configuration of the

network to configure the neighbor and forwarding table. However, the relative overhead frequency decreases substantially after the first hour because only the HELLO messages would provide the information needed to the sender nodes to update their transition probabilities. On the other hand, the relative frequency of LCBR and OSDRP is higher due to the frequent calling the route recovery and spectrum assignment mechanism.

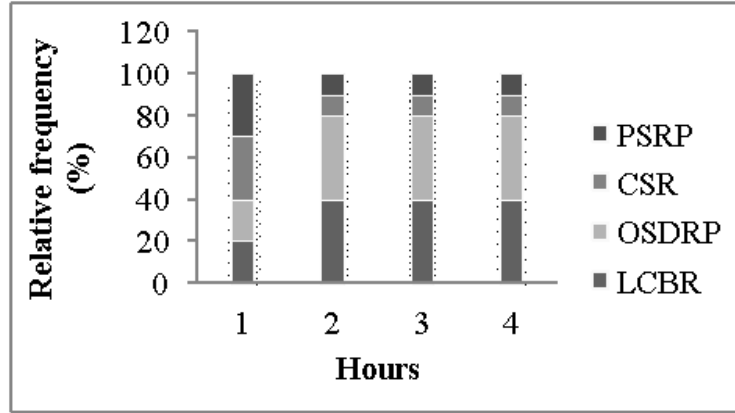


Figure 5.6 Relative frequency distribution of overhead in the first 4 hours of network operation.

5.4 Summary

In this chapter, we introduced the Primary Spread Aware Routing Protocol (PSARP), which is able to adapt to the uncertainties of spectrum availability in cognitive radio networks. PSARP is based on the Markovian property of a particular flow from source to destination and uses PWM as one of its routing metrics. We demonstrated through simulation that PSARP is robust to the variation of the primary users' activity. Our results confirmed that using a stochastic protocol for a stochastic environment is indeed more cost efficient and suitable than using deterministic protocols that map channels' availability to nodes' availability. We believe this research is the beginning of a new line of work on the development of stochastic routing protocols.

Chapter 6

Decision Tree Cognitive Routing

In the previous chapters we explained that in a dynamic CRN, the arrival rate of primary users is high, causing small windows of spectrum usage opportunity. High variations in spectrum opportunities produce uncertainties in the problem of spectrum sharing and routing. In this chapter, we focus on developing another routing scheme that works under such uncertainties.

It is indeed plausible to adopt elaborate techniques in statistics that address decision making problems in an environment where uncertainty exists and the true state cannot be fully predicted. This is exactly the situation of a cognitive radio sender. First, the variety of spectrums and their corresponding channels provide multiple routes from the server to the client. Hence, the server has multiple options with different routing consequences. Second, the chosen route might not stay stable during the transmission period. Therefore, the sender node is uncertain about the consequences of its decision. In other words, the circumstances governing a node's decision might change. The theory of games and decision theory deal with decision making problems under uncertainty. In game theory the players play against each other. Each player wishes to maximize its fortune. This theory is intensively used in networks [14]. In decision theory a player plays against nature, meaning the player opponent does not try to increase its fortune, but exhibits stochastic performance that is explained by probability laws. In decision theory the current state of the game is taken to be uncertain and the decisions are made considering such uncertainties. In a highly dynamic environment, decision theory leads to less computational complexity than game theory since many types

of games have multiple equilibria under such variations. In this chapter, we bring the problem of routing in a dynamic CRN to the framework of a decision making problem. Then, backward induction terminal analysis is used to produce the decision strategy for a sender node.

To translate routing in CRNs into a decision problem, notice that in a CRN, a sender does not have a full knowledge of the availability and stability of the neighboring nodes due to the instability of available channels. The sender information is expressed by two probability distributions, called prior and posterior distributions. A prior distribution governs and explains the natural status of the states (neighboring nodes) unknown to the decision maker (sender). A posterior distribution gives the sender understandings of unknown states after performing an experiment that gives partial additional information on the status of the unknown states. A utility function also indicates the decision maker gains or losses. Decision data is usually denoted by (e, z, a, s) . The decision maker runs experiment e , observes sample z , takes act a when the true state is indeed s . An optimal act minimizes the expected loss or maximizes the expected gain; the latter equals to $\max_e E_{p(z|e)} [\max_a [E_{p(s|z,e)} U(e, z, a, s)]]$, where $p(z|e)$ is the marginal sample distribution for e , $p(s|e, z)$ is the posterior distribution, and $U(e, z, a, s)$ is the utility function. When the decision maker does not perform an experiment, $p(s) \sim p(s|e_o, z_o)$ stands for the prior distribution, while e_o, z_o means no experiment, no observation.

One important challenge is to propose appropriate posterior distribution. This will give weight to the sampling and reduces the cost due to uncertainty. It is understood in Bayesian statistics that a good posterior ultimately and efficiently will estimate the unknown parameters. However, in cognitive radio networks the classical statistical distributions cannot be used as default probability laws governing the sender realization of the status of the channels connecting it to its neighboring nodes. This is due to the non-stationary presence of primary users. The performance of the ArgMax distribution [59] motivates one to build the empirical ArgMax distribution that acts as a sample

distribution. Then the posterior distribution is easily deduced. This nicely and effectively provides the sample information to the sender, and is one of the contributions of this work.

The utility function also plays a crucial role in taking into consideration the side issues that are imposed on a decision problem. In routing, it is vital to design a correct utility function, as it affects the overall routing performance. We form a utility function, formula (8.1) in subsection 6.1.4, which is equipped with different control knobs that adjust the gain by changing the significance of parameters associated with spectrum stability, node reliability and bandwidth variability.

By adopting the decision problem components, we build a Decision Tree Cognitive Routing scheme (DTCR) that aids a sender node in selecting the most appropriate next hop neighbor in terms of stability and reliability. In summary the contribution of this chapter is as follows:

- We develop a decision tree cognitive routing scheme to model and analyze the problem of routing in a dynamic CRN.
- We construct appropriate sample and posterior distributions to explain the status of channels and nodes in supporting packet delivery.
- We introduce a utility function that captures the effects of spectrum availability, bandwidth fluctuations and path quality. This utility function is expandable to include other important decision making factors.

We compare the performance of our DTCR strategy with the optimal strategy. In the optimal strategy, nodes have full knowledge of the future changes in the network parameters. In other words, no routing strategy performs better than the optimal strategy. We also compare our method with the local coordination based routing and spectrum assignment protocol [58] to measure the deviation of our scheme and a routing protocol designed for a dynamic environment from the optimum strategy. We like to emphasize here that the DTCR is specifically designed for dynamic

distributed cognitive radio networks, therefore choosing a semi dynamic routing protocol would not provide us with a fair comparison. Our results show that our DTCR successfully treats the occurrence of uncertainty and performs close to the optimal scenario. The DTCR uses the posterior probability distribution to estimate the availability of a neighbor under uncertainty. The backward induction scheme helps a node to choose a neighbor that is more likely to be the correct candidate; it reduces the cost of choosing wrong candidates. Therefore it operates substantially better than the local coordination based routing protocol; its performance is indeed near optimal at low and moderate sending rates. However, at high sending rates, it still outperforms the local coordination based routing.

The organization of this chapter is as follows. In Section 6.1, we present the decision theory frame work and DTCR utility function. The terminal analysis backward induction and its use in obtaining a correct decision in our strategy is discussed in Section 6.2. Section 6.3 presents the details of implementation and simulation results.

6.1 System Model

We consider the mesh cognitive radio network in section 4.3 that is installed in an urban area. Nodes have access to multiple spectrum bands and are able to choose any channel from those spectrum bands. The diversity of the clients and the available spectrum bands result in a fairly dynamic operating environment. The variety of spectrums and their corresponding channels provide multiple routes to the gateway. However, the chosen route might not stay stable during the transmission period. Therefore, it cannot be guaranteed that the packets will reach the destination. In such an environment, an end-to-end path does not provide a feasible solution. In our strategy a node only decides among its neighbors and the quality of the remainder of the path to the gateway

is translated by the amount of weight allocated to the neighbors.

We assume the channel is shared with a Non-Contiguous Orthogonal Frequency Division Multiplexing (NC-OFDM) technique, which is sufficiently agile with respect to spectrum usage. By deactivating (i.e, nulling) subcarriers that can potentially interfere with other users, this form of OFDMA fills in the available spectral gaps within the channel's transmission bandwidth partially occupied by other users while not sacrificing its error robustness [47].

Similar to previous chapters, the fluctuation of the wireless channel is modeled by the Rayleigh fading model.

A mesh cloud with a single gateway with four different spectrum bands is shown in Figures (6.1a) and (6.1b). For simplicity, nodes located within the same number of hops from the gateway are grouped into one layer. We refer to a node i in a layer l as $i[l]$, $i = 1, 2, \dots, M$, where M represents the total number of nodes in the network. The node $i[l]$ chooses a node that is located either in its own layer l or in the upper layer $l - 1$, and is inside its radio transmission range. Let N_i denote the number of candidate nodes available for node $i[l]$.

Table 6.1 summarizes the notations that are used in this article. For simplicity, we suppress the notations l and t , and use i and $k_{i,j}$ whenever there is no ambiguity. Let us assume that the node 12[4] in Figure (6.1b) has packets to send to the gateway. Based on the spectrum coverage and node 12[4] radio range, this node has 3 intermediate neighbors: 8[3], 9[3] and 11[4]. Node 12[4] chooses one of its neighbors. In terminology of decision theory [16], the set of possible states (choices) available to the decision maker i is represented by $\mathcal{S}_i = \{s_1, s_2, \dots, s_{N_i}\}$. The node 12[4] is the decision maker. The states unknown to the decision maker are the intermediate neighboring nodes, $s_1 = 8[3]$, $s_2 = 9[3]$ and $s_3 = 11[4]$. Therefore, $\mathcal{S}_{12} = \{s_1, s_2, s_3\}$. There is also a set of actions that the decision maker can take, represented by $\mathcal{A}_i = \{a_1, \dots, a_{N_i}\}$; a_ν is the act of choosing a state s_ν to visit. According to our example, we have three acts, a_1, a_2, a_3 ; a_ν corresponds to

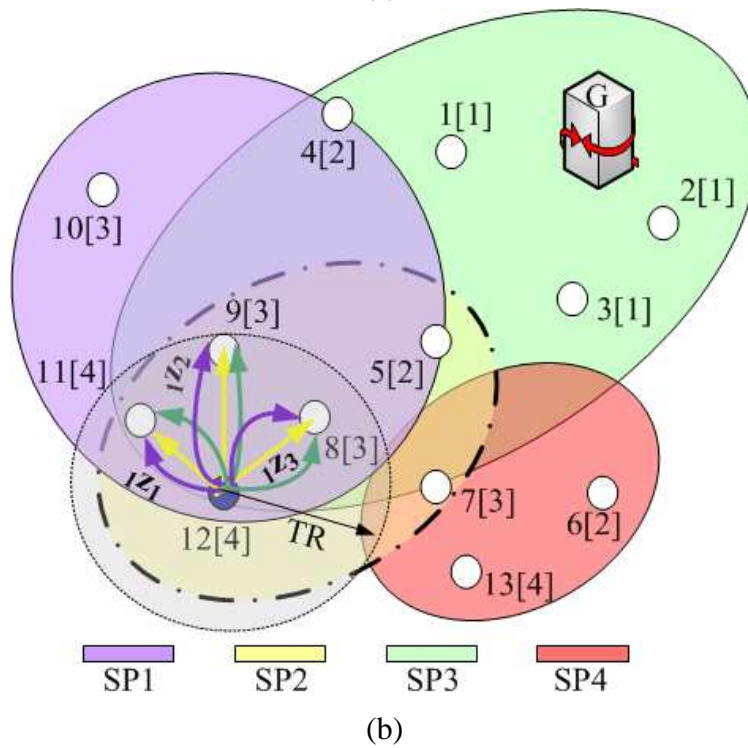
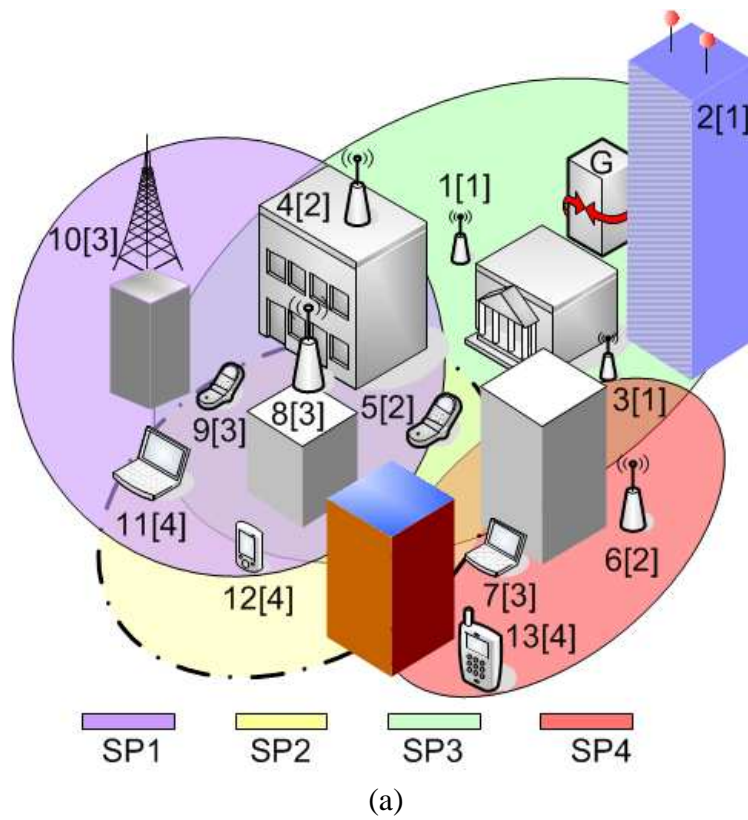


Figure 6.1 A simple mesh cloud within a city with its node diagram

choosing a neighbor s_ν , $\nu = 1, 2, 3$.

Table 6.1 DTCR Notations

\mathcal{S}_i	Decision state space of node i .
\mathcal{A}_i	Decision action space of node i .
\mathcal{Z}_i	Decision sample space of node i .
e	The experiment of assessing the duration of channel availability between the sender and its neighbors.
e_0	No experiment.
$i[l]$	Node i in layer l ; l hop away from the gateway.
$k_{i[l],j[l']}(t)$	channel k between node $i[l]$ and $j[l']$ at time t .
$N_{i[l]}$	Number of neighbors available for node $i[l]$.
M	Total number of nodes in the network.
$i z_j$	Maximum duration of channels availability in spectrums between node i and neighbor j .
a_j	The act of choosing node j .
(e, z, a, s)	Branch of the tree corresponding to the experiment e that leads to sample z taking action a when the true state is s .
$u_i(e, z, a, s)$	Utility function corresponding to the branch (e, z, a, s) .

In the initial learning phase the sender gathers information from their neighbors and their surrounding spectral measurements to construct the decision tree (refer to Section 2.5). The *decision tree* is a technical term in statistical theory [16] and should not be misinterpreted by a routing tree or a graph theory tree. The decision tree demonstrates all possibilities in a decision making problem. Figure 6.2 shows the decision tree associated to the decision making of the node 12[4]. The node 12[4], sits at the root of the tree and the states are at the ending branches of the tree. In the beginning of any decision problem, the decision maker can perform an experiment to obtain additional information in support of an act. Performing an experiment e is not obligatory and the node may go for e_0 , which means no experiment. The experiment here, is sensing the duration of availability of channels connecting the node 12[4] to its neighbors. The possible outcome of the experiment is $12 z_j$, the maximum duration of channels availability in spectrum bands between

node 12[4] and neighbor j . The outcome of e_0 is z_0 , corresponding to no observation.

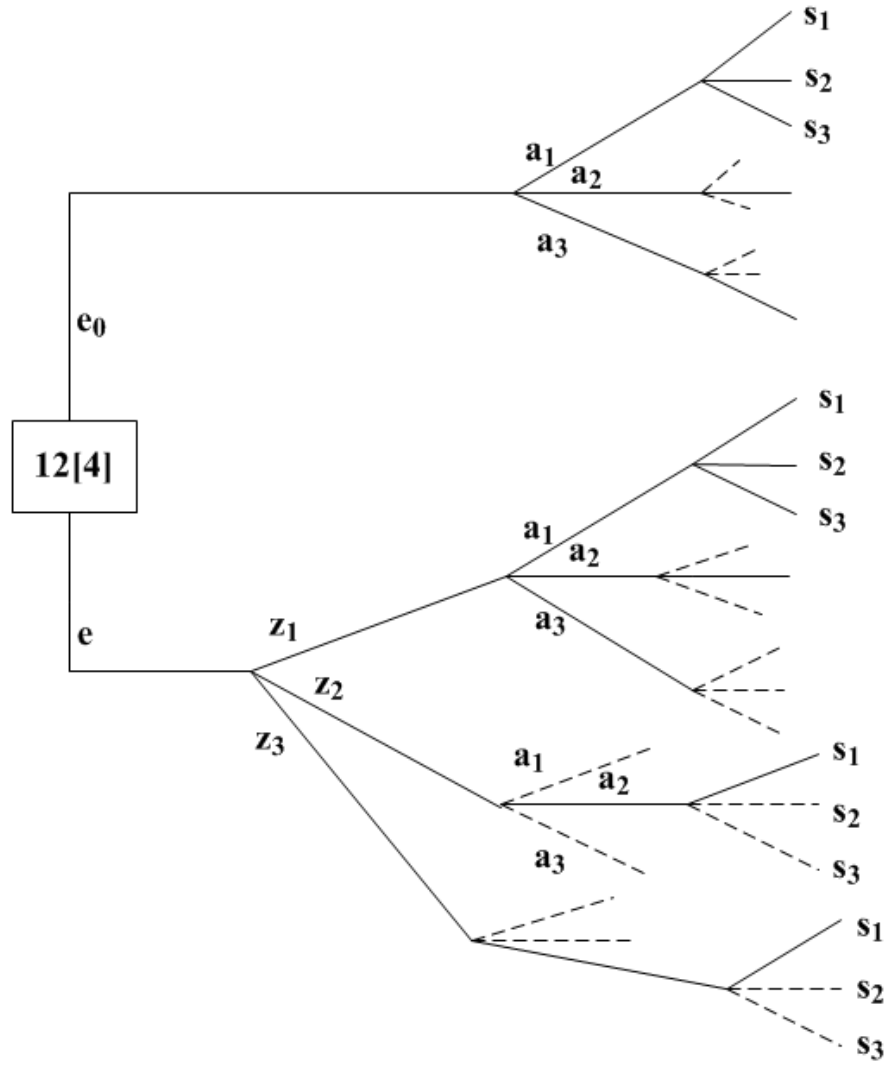


Figure 6.2 Node 12 decision tree, with three states and three acts

6.1.1 Experiment e

Performing an experiment in decision theory means that the decision maker is willing to give some cost in exchange for gaining partial information about the status of the unknown states. The experiment e is collecting and reading a history of primary users' activities on its surrounding channels, then measuring the maximum duration of channels availability $12z_j$ in spectrum bands

between the node 12[4] and its neighbor j . Many previous studies in routing also rely on past measurements on the activities of primary users to find the most stable path [33, 60].

We assume that there are $K_{i,j}$ spectrum bands available between nodes i and j . Each spectrum band has a number of channels. Node $i[l]$ handshakes with its neighbor node j , $j = 1, 2, \dots, N_i$, and receives the signal-to-noise ratio gain ($SNRg_{k_{i,j}}(t)$) of a channel $k_{i,j}$ of that spectrum band, which connects node $i[l]$ to the node $j[l - 1]$. The $SNRg_{k_{i,j}}(t)$ is evaluated at the neighbors' receiving antennas. The $SNRg_{k_{i,j}}(t)$ at time t is the signal-to-noise ratio, SNR , of a shared channel over the SNR of the same channel when it is not shared by other users. Hence, the $SNRg_{k_{i,j}}(t)$ roughly indicates the occupancy influence on the channel. Based on [47], the occupied bandwidth of the channel $k_{i,j}$, denoted by $O_{k_{i,j}}$, is given by:

$$O_{k_{i,j}}(t) = B_{k_{i,j}} \sqrt{10^{(-SNRg_{k_{i,j}}(t)/10)}}, \quad (6.1)$$

where $B_{k_{i,j}}$ is the bandwidth of the channel $k_{i,j}$ in Hz. Therefore the period of occupancy on the channel $k_{i,j}$ approximately is:

$$Y_{k_{i,j}}(t) = 1/O_{k_{i,j}}(t). \quad (6.2)$$

Let us denote the duration that the channel $k_{i,j}$ is sensed idle by the random variable $X_{k_{i,j}}$. Then the duration of channel availability is $T_{k_{i,j}} = X_{k_{i,j}} - Y_{k_{i,j}}$

Finally, node i stores the maximum observed duration of channel availability in the spectrum bands between itself and each of its neighboring nodes, into a vector R_i :

$$R_i = \begin{pmatrix} {}_i z_1 & {}_i z_2 & \cdots & {}_i z_{N_i} \end{pmatrix}. \quad (6.3)$$

The variable ${}_i z_j = \max_{k_{i,j}} T_{k_{i,j}}$ shows the maximum observed duration of channel availability in the spectrums between node i and j . The variable ${}_i z_j$ is a sample observation in favor of

neighbor j . Therefore, the node 12[4] in our simple mesh network, Figure (6.1b), constructs the following record.

$$R_{12} = \begin{pmatrix} 12z_1 & 12z_2 & 12z_3 \end{pmatrix}. \quad (6.4)$$

The record vector R_i is used to construct a sample and ultimately a posterior distribution for the maximum spectral channel availability durations as follows.

6.1.2 A Sample Distribution

We quantify the stability of the spectrum bands and their corresponding channels by using the ArgMax probability distribution introduced in Chapter . In [59], the authors show the accuracy of the ArgMax distribution in targeting the most stable channel. From the perspective of node i , $iz = \max_j iz_j$ is the quantity of the sampling interest. The ArgMax probability distribution for a neighbor node j^* is the probability that the node j^* contributes iz_{j^*} . The sampling distribution is the ArgMax distribution whenever the neighbor node that has the maximum available channel duration is j . We denote the sampling distribution by $p_i(j^*|j)$, $j^*, j = 1, 2, \dots, N_i$.

The sampling distribution is estimated by the corresponding empirical distribution as follows: After the ArgMax distribution is estimated for a single realization of available channel durations at each node (see algorithm (2) in Section 6.3) then the procedure will be repeated for many realizations. The sampling ArgMax probabilities are classified according to nodes assuming maximum ArgMax probabilities. Then the sampling distribution is obtained by finding the mean vector of each class. The result will be an $N_i \times N_i$ matrix, where the j -th column stands for the estimated sampling distribution whenever j is the true (state) neighbor node. Let us make a brief demonstration. Let $N_i = 3$ and the ArgMax probabilities for 6 realizations to be: [.3 .5 .2], [.6 .1 .3], [.2 .7 .1], [.8 .1 .1], [.3 .6 .1], [.2 .3 .5]. The realization $\{[.6 .1 .3], [.8 .1 .1]\}$

are assigned to node 1, the realizations $\{[.3 \ .5 \ .2], [.2 \ .7 \ .1], [.3 \ .6 \ .1]\}$ are assigned to node 2, and $[.2 \ .3 \ .5]$ is assigned to node 3. The sampling distribution will be the 3×3 matrix:

$$p_i(j^*|j) = \begin{pmatrix} .7 & .266 & .2 \\ .1 & .6 & .3 \\ .2 & .134 & .5 \end{pmatrix}. \quad (6.5)$$

6.1.3 The Posterior Distribution

Now that the sample probabilities $p_i(j^*|j)$ are constructed, the decision maker can compute the probability that neighbor node j is the true node whenever his sample indicates that j^* is the appropriate state. In other words, the node j is the true neighbor to send to but the outcome of the experiment is in favor of j^* . This is indeed the posterior distribution on the neighboring nodes, and is given by

$$p_i(j|j^*) = \frac{p_i(j^*|j)p(j)}{\sum_j p_i(j^*|j)p_i(j)}, \quad (6.6)$$

where $p_i(j)$ is the priori distribution on the neighboring nodes. In our design the prior distribution of a neighbor node j is proportional to the total number of channels that connects it to the sender.

Note that the denominator in the above equation is the marginal sample distribution. This probability distribution will be used in our backward induction procedure.

6.1.4 Utility Function

A utility function assigns a quantity (gain) to a decision datum (e,z,a,s). In a decision problem, a utility function is either given or is formed to explain gains for correct decisions and losses for wrong decisions, by taking into consideration the cost of sampling. Although a utility function can take negative values, in practice, it is adjusted or transformed so that it assumes only nonnegative

values. Naturally for fix s , the utility function attains its maximum at decision data (e_0, a_s, s) , where e_0 is no experiment, and a_s is the trivial immediate act. The decision maker chooses a_s if he knows the true state is s . Sampling cost as well as incorrect or inappropriate acts will reduce the gain.

In our routing modeling, we go for zero-one scenario, in the sense that wrong selection of the node is a total loss, i.e. zero utility. Thus we let

$$\mu(a, j) = \begin{cases} 1 & \text{if } a = j, \text{ when } j \text{ is the true state,} \\ 0 & \text{if } a \neq j, \text{ when } j \text{ is the true state.} \end{cases}$$

Consequently

$$u_i(e_0, a, j) = \eta_j \mu(a, j), \quad (6.7)$$

where η_j is a constant that reflects the transferring quality of node j specified by the remaining queue capacity of node j . We let the maximum gain be reduced by the factor $1 - e^{(-\gamma_i z_j^*)}$ due to the sampling cost, where z_j^* is a sample and γ_i is the controlling factor to quantify the amount of channel availability variation from the sender perspective. Depending on the sensitivity of the application on the bandwidth fluctuation, γ is selected. For example, when γ is around 0.5, a small difference in the duration of channel availability would provide a significantly higher gain and the node is encouraged to choose the node with highest duration of availability. Although sampling is expected to some extent guide one to the true state, it may not always point to the optimal act. Such a deviation will reduce the gain. The factor $V(a, a_j^*)$ is for the corresponding reduction. We assume that

$$V(a, a_j^*) = e^{-\beta [Ae(a) - Ae(a_j^*)]^2}, \quad (6.8)$$

where $A_e(a)$ is the gain associated with choosing the right act a and $A_e(a_j^*)$ is the gain of choosing the act a_j^* following observing the sample j^* . In our work $A_e(a)$ will be the maximum duration of channel availability. The parameter β is the knob that controls the significance of the amount of gain associated with relying on the spectrum measurement. If β is small, a node may be chosen that does not necessarily have the highest duration of channel availability. In other words, β acts as an error tolerance factor in channel availability measurement. By considering the fact presented above, our utility function assumes the following formulation.

$$u_i(e, j^*, a, j) = \eta_j [1 - e^{(-\gamma_i z_j^*)}] [v(a, a_j^*) \mu(a, j)]. \quad (6.9)$$

As mentioned previously, the environmental dynamics of the cognitive radio network might change and the node might choose a neighbor that was not the most appropriate node in routing. The indicator function μ is chosen to model the gain/loss for such a scenario. Note that based on μ , we assume total loss when a wrong node is selected to transfer packets. A wrong node would not necessarily give a total loss but may be able to transfer some packets based on its queue capacity. An interesting future direction is to model μ according to nodes' queue length.

6.2 Making a decision using Backward Induction

After the construction of an appropriate decision tree for our routing problem, the optimum strategy (course of action) is specified by a branch that leads to the maximum average utility. It is specified by *the backward induction terminal analysis*.

Backward induction is to work back from the ending branches of the decision tree to the initial starting point (root). The decision data (e, j^*, a, j) are eliminated one at the time. Random data j

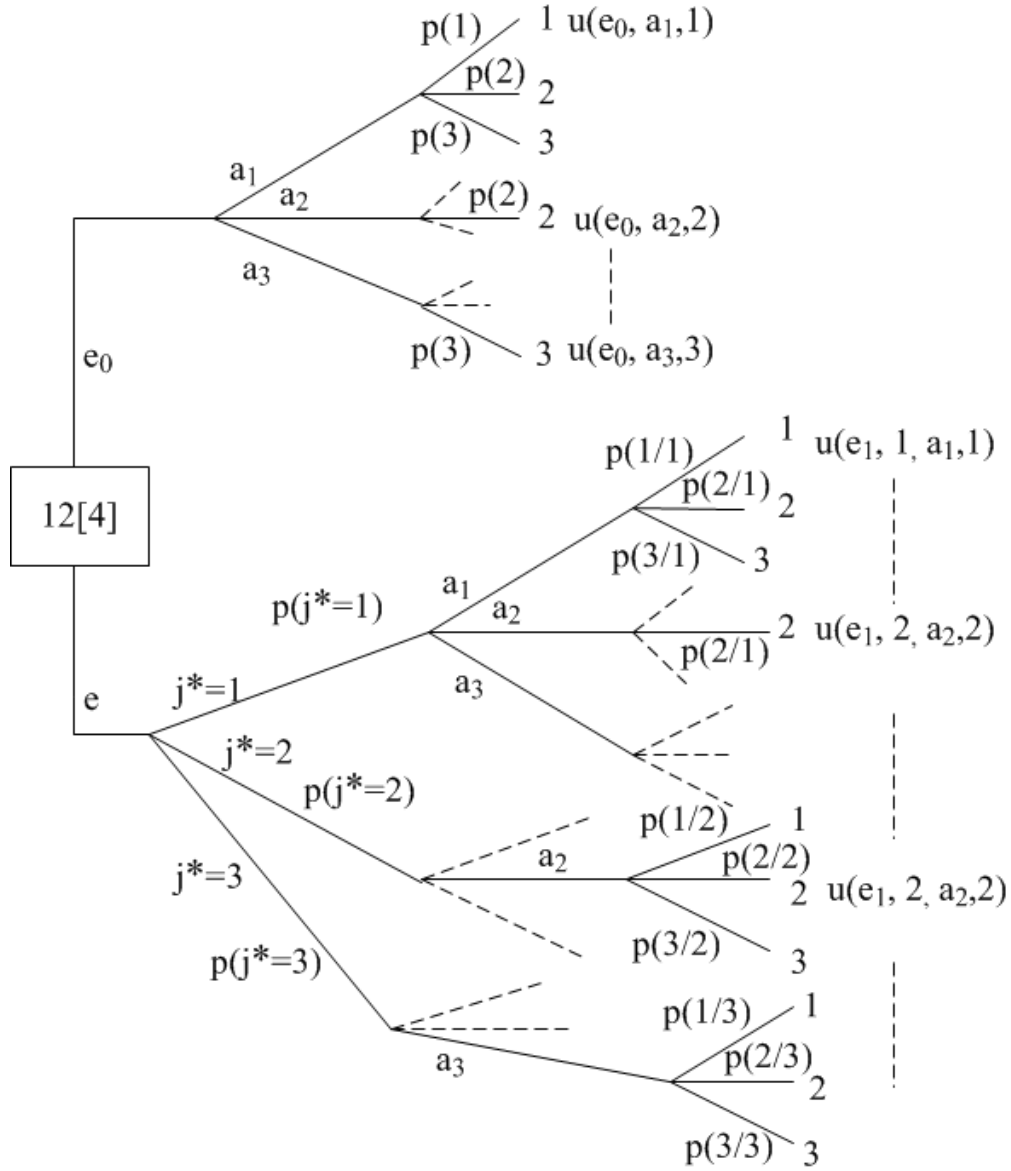


Figure 6.3 Node 12 decision tree with some utilities

and j^* are eliminated through expectations; deterministic and optional data a and e are eliminated using maximizing process.

The first step is to find the expected utility with respect to the state distributions.

$$Eu_i(e, j^*, a) = \sum_j u_i(e, j^*, a, j)p(j|e, j^*), \quad (6.10)$$

$$Eu_i(e_0, z_0, a) = \sum_j u_i(e, z_0, a, j)p(j|e_0, z_0), \quad (6.11)$$

where the state distribution $p(j|e_0, z_0)$ for the experiment (e_0, z_0) is the prior distribution, and $p(j|e, j^*)$ is the posterior distribution. The second step is to identify the optimal act a_j^* for the experiment e and outcome j^* , defined by

$$Eu_i(e, j^*, a_j^O) = \max_a Eu_i(e, j^*, a). \quad (6.12)$$

The maximum expected utility is $Eu_i(e, j^*, a_j^O)$. We let $I(e_0) = \max_a Eu_i(e_0, z_0, a)$, $I(e_0)$ be the maximum expected gain under no experiment.

The third step is to use sample information by taking expectation of the maximum expected utility for the optimal a_j^O with respect to the marginal sample distribution:

$$I(e) := E \left\{ Eu_i(e, j^*, a_j^O) \right\} = \sum_z \left\{ Eu_i(e, j^*, a_j^O) \right\} p_i(j^*). \quad (6.13)$$

Recall that $p_i(j^*) = \sum_j p_i(j^*|j)p_i(j)$ is the marginal sample distribution. The $I(e)$ is the maximum expected gain under experiment e .

Finally $I = \max\{I(e_0), I(e)\}$ specifies the total utility index. The branch that corresponds to the index I and optimal act a_j^O specifies the right neighbor.

The backward induction procedure for our simple mesh network is depicted in Figure 6.4. After following the above steps, the course of action in this example is through experiment e because $I(e) > I(e_0)$. Then for $j^* = 1$ choose $j = 3$ since $E_S U(e, 1, a_3)$ is maximum among other branches extended from observing $j^* = 1$, and for $j^* = 2$, choose $j = 1$, and for $j^* = 3$, choose $j = 3$ for the same reasoning as above. As we see in this simple example, collecting the samples and evaluating the sample and posterior distribution is needed in the initial learning phase of the DTCR strategy. After this initial learning, the decision maker only decides its next hop by a saved

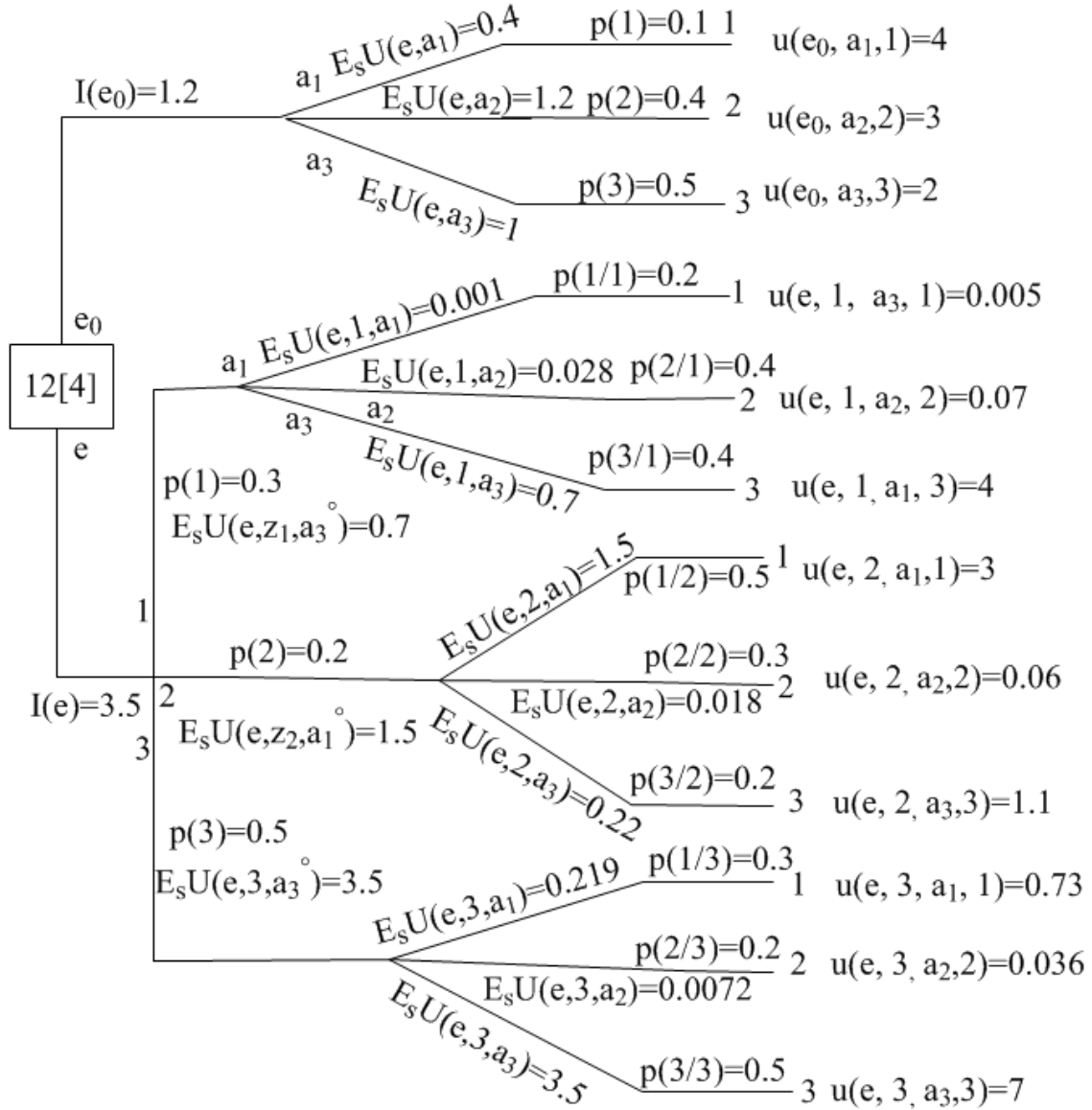


Figure 6.4 Node 12 decision tree

strategy developed in the learning phase. This is the reason that the DTCR is adaptable to the changes in a highly dynamic environment. After the learning phase, it understands the dynamics by relying on having only one sample observation which is available from any MAC protocol and chooses the next hop according to the saved procedure.

6.3 Simulation

In this section we present the details of implementing our decision tree cognitive routing scheme and the results of simulation. In our simulation setup we are able to explore larger size networks with a variable range of parameters more effectively than what is possible in existing testbeds. The simulation parameters and the traffic patterns are chosen based on measurement analysis done on real networks. We have the capability to derive actual workload patterns from a network that operates in a highly dynamic environment.

6.3.1 Implementation Details

Our topology is similar to Figure 6.1b. There is a single gateway and nodes are arranged into layers based on their number of hops from the gateway node. The number of accessible nodes N_i varies depending on the radio signal strength. A random value is assigned for the radial distance of node i from node j . If node j is within the radio transmission range of node i , it is considered accessible by node i . In our simulation model we have $K = 5$ spectrum bands. The range of their corresponding bandwidth changes from 6Mb/sec (which could correspond to the FM radio band) to 144Mb/sec (similar to a TV channel). Note that a spectrum band depending on its type could have a different number of channels. The bandwidth of each spectrum is divided equally among its channels. For example, the 144Mb/sec spectrum band has 6 channels, each with a bandwidth of 24 Mb/sec (similar to sub CATV band).

To demonstrate the effect of primary users on channels, we generate random numbers from an exponential distribution with parameter λ . As λ gets larger, the amount of time that the PU is not using a channel is less. Once the channel is available, it is shared among other users. Based on a measurement study [50], the occupied portion of the channel is modeled by a lognormal distri-

bution with mean μ and standard deviation σ . The larger the value of μ , the more occupied the channel would be. The duration of channel availability ${}_iz_j$, can be found by using a truncated distribution when the occupied portion of the channel is available, refer to Section 4.2. The record R_i is constructed by collecting the maximum duration of channel availabilities from each spectrum band for each neighboring node and discarding the rest. Using R_i record, the ArgMax probability $p_i({}_iz_j)$ is evaluated empirically using algorithm 2. The variable T_{max} corresponds to the length of the sensing period. The ArgMax probability distribution is updated and evaluated every τ seconds. The variable τ decreases if the decision procedure indicates no testing is necessary according to the dynamics of the network. In other words, no new records need to be collected. The sensing period of channels could also be controlled according to network dynamics in future designs. As explained in the previous section, in the initial phase of network operation (learning

Algorithm 2 ArgMax probability calculation procedure

```

for  $t = 1$  to  $T_{max}$  do
  in  $R_i(t)$ 
  if  ${}_iz_j$  is maximum then
     $Max_j = Max_j + 1$ 
  end if
end for
 $p_i({}_iz_j) = Max_j(t)/t$ 

```

phase), a sender constructs a decision tree on the set of its neighboring node. It evaluates the best decision strategy based on backward induction to consider future uncertainties. After the initial phase (operation phase), a node only looks at its R_i record at time t and makes its decision, based on its current sensing observation. Algorithm 3 summarizes the steps of the decision tree cognitive routing procedure in each phase.

In the above algorithm, the end of the operation period depends on the node's mobility, traffic arrival rate and other network design factors. For a fairly static network, where nodes disappear

Algorithm 3 Decision tree cognitive routing procedure

Require: $p_i(j)$, R_i , $p_i(i z_j)$ records.

Initial learning phase:

Evaluate $p_i(j^*|j)$ using the ArgMax probability distributions $p_i(i z_j)$.

Using multiple R_i records, evaluate utilities based on equation (8.1).

Evaluate $p_i(j|j^*)$ and $p_i(j^*)$ using $p_i(j^*|j)$ and $p_i(j)$, equation (6.6).

Use the backward induction steps in Section 6.2 and get the decision strategy.

if $I(e_0) > I(e_1)$ (taking e_0 branch) **then**

Decrease the nodes sensing period.

else

Save the decision strategy.

end if

Operation phase:

At time t look at the R_i

if $i z_j$ is maximum **then**

Look at the saved decision strategy, get the case when $i z_j$ is observed and choose the next node accordingly.

end if

Switch to initial phase when operation period is ended.

due to their expected battery life, the operation period could be weeks. Note that any uncertainty due to different environmental parameters is already counted in the initial learning phase. The operation period can also be controlled adaptively. For instance, when the gateway throughput is falling below a certain predefined threshold, a flag is sent to the nodes to enter the initial phase and change their decision strategy.

In our simulation, our nodes update their decision strategy every 4 hours and the simulation ran for 12 hours. Every 300 seconds the radial distance of nodes changes, meaning the set of neighbors changes for a particular sender node. Based on study [50], we use an exponential distribution with mean $\lambda = 1/3$ to model the arrival rate of primary users. We consider a lognormal distribution with means 0.8, 0.2, 0.5 and 0.5 variance to model heavy, moderate and light users on channels, respectively.

We compare our decision framework with an optimal strategy. In the optimal strategy, nodes have complete knowledge of the future changes in the network states. In other words, this is

the best performance that the network could have with its queue length, number of channels and packet arrival rate. We are also interested in making a comparison between the deviation of DTCR and other protocols from the optimum strategy. As explained in the related work, many routing protocols designed for dynamic CRNs use the framework of ad-hoc networks. We used the local coordination based routing and spectrum assignment protocol [58], which is an AODV based protocol that uses the summation of frequency switching and back off delay at a node on top of the number of hops as its routing metric. The protocol also identifies traversing flows at each node and calculates the active frequency bands taken, which are used for multi-flow multi-frequency scheduling. As mentioned in the related work, many other schemes that are designed for the dynamic environment adopt the same approach. The performance of this protocol is shown by using the abbreviation of Secondary Option Protocol (SOP) in our simulation results. Since we are considering a dynamic environment, DTCR is not compared to other protocols such as CRP [60] designed for a semi dynamic environment.

6.3.2 Effect of Network Load

To test the decision strategy under various network loads, we used 78 nodes in our network, distributed randomly in a 1500×1500 sqm field. There are 12 sources and a single gateway. The sending rate of the sources is changed from 1Mb/sec to 7Mb/sec. The MTU size is 2000 bytes. The average throughput and delay with their 95% confidence intervals are shown in Figure 6.5 and Figure 6.6. The environment is highly dynamic with the average OFF period of primary users $\nu = 3sec$.

The DTCR procedure is more successful in capturing the uncertainties than the Secondary Option Protocol (SOP). In SOP the routing tables are not updated frequently enough and the repetition of calling the route request mechanism results in transmission delay and packet loss. DTCR op-

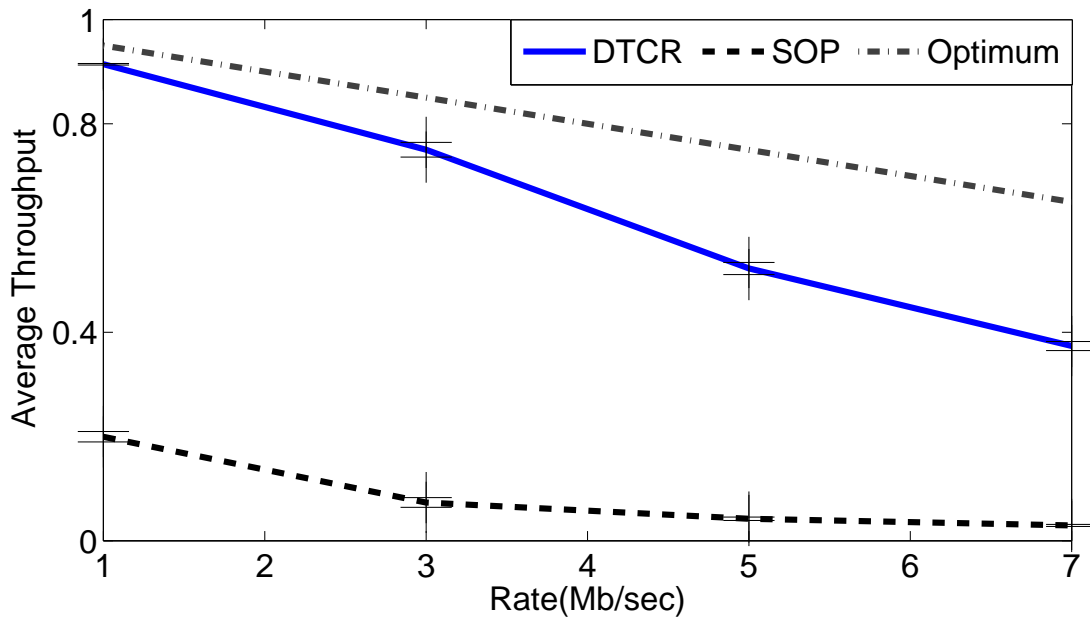


Figure 6.5 Average throughput with 95% confidence interval for different sending rate, size = 78 nodes

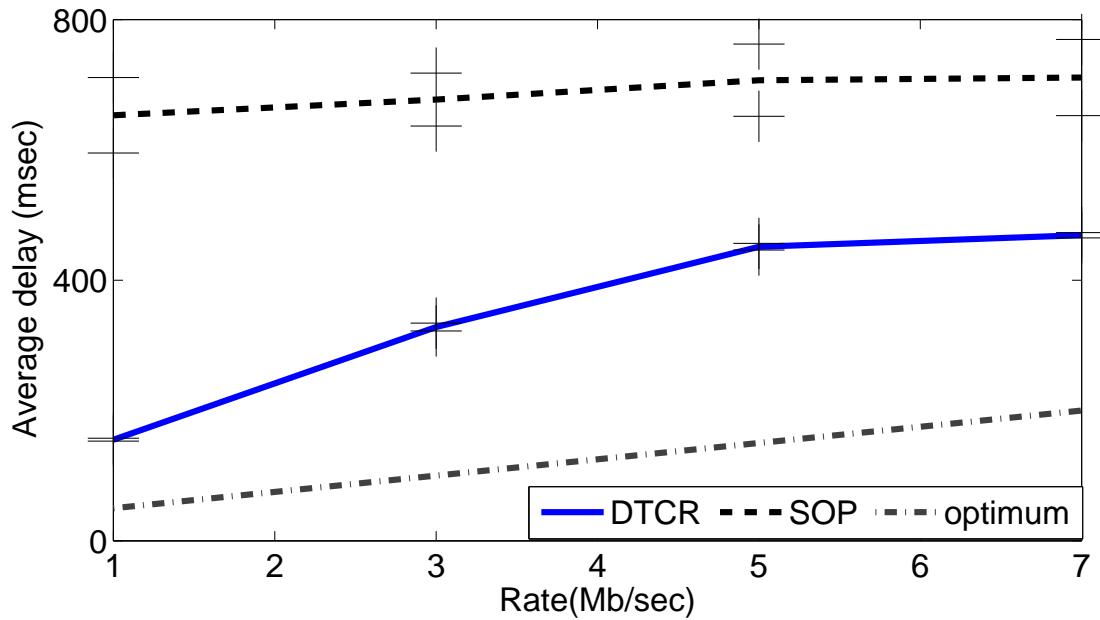


Figure 6.6 Average throughput with 95% confidence interval for different sending rate, size = 78 nodes

erates near optimum when the rate is below 3Mb/sec. After this rate, the DTCCR performance is lower because as the rate increases, the variation in channel opportunities is larger and nodes have

to adjust their decision making more quickly. In most of the applications, the sending rate does not exceed the 3Mb/sec rate. In addition, there are many controlling parameters such as $0 \leq \beta, \gamma \leq 1$, the length of the operation period and the sensing period in DTCR that can be adjusted to achieve the desired performance. One interesting future direction is to find the optimum value of these parameters by solving a classical optimization problem at each layer with the objective of maximizing the gain $I_i(\beta, \gamma)$, see Section 6.2. In the last subsection, we elaborate on the effect of control knobs in the utility function of DTCR and its decision making. We experimentally tried different values for β, γ in their corresponding ranges to achieve better performance at the gateway.

6.3.3 Effect of Network Size

We also changed the network size from 30 to 78 nodes, and kept the sending rate constant at 2Mb/sec, and $\nu = 3sec$. Figure 6.7 and Figure 6.8 show the average throughput and end-to-end delay with 95% confidence intervals. Since DTCR is decentralized, network size does not affect the performance significantly. The performance of SOP drops significantly since the end-to-end path is highly unstable.

6.3.4 Primary Users Traffic Patterns

We changed the primary users arrival rate λ and decreased it to create a semi-dynamic environment. In table 6.2, variable $\nu = 1/\lambda$ indicates the mean OFF time of the primary users. The network has 78 nodes and the sending rate is 2Mb/sec. We see that the SOP protocol performance improves significantly. DTCR is still able to adapt to the changes in the environment. The performance is closer to the optimum scenario. We would like to emphasize here that our design is tailored towards a dynamic environment but we also foresee the DTCR working satisfactorily in a semi-dynamic

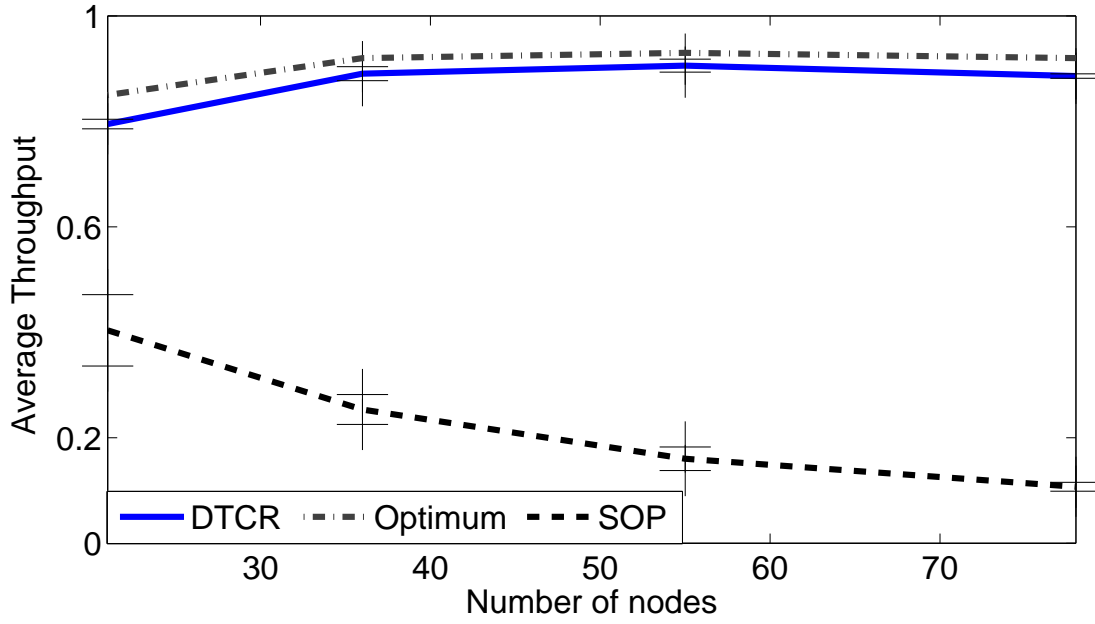


Figure 6.7 Average throughput with 95% confidence interval for different network size, sending rate is $2Mb/sec$

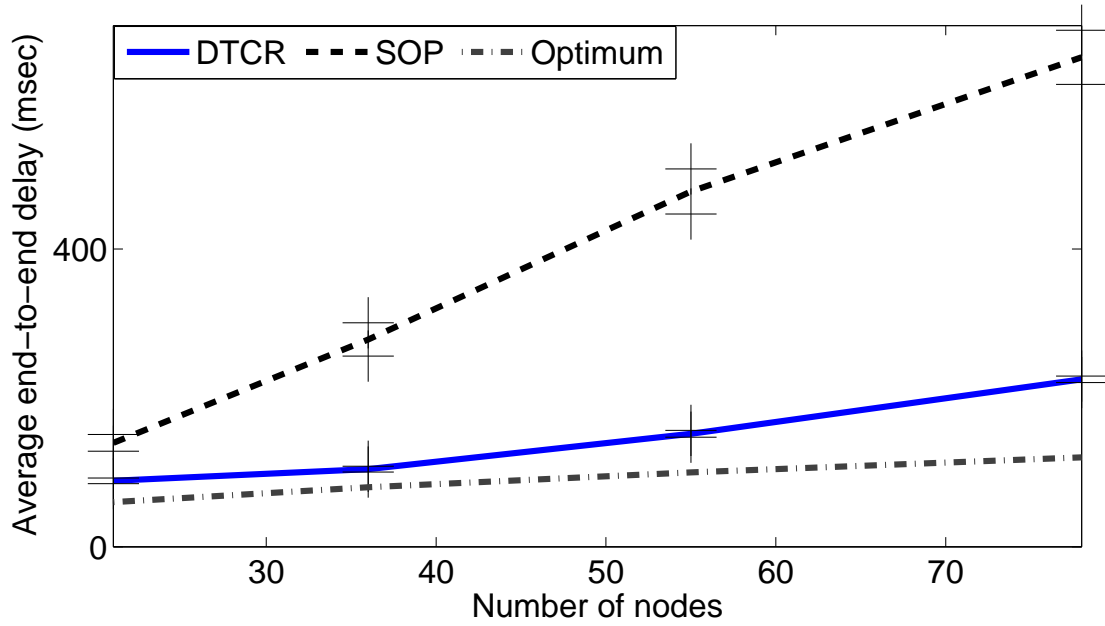


Figure 6.8 95% confidence interval of average end-to-end delay for different network size, sending rate is $2Mb/sec$

environment.

6.3.5 Adjusting the DTCR Parameters

In the utility function described in Section 6.1.4, three control parameters β, γ, η exist that quantify the importance of local spectral measurement, its variation and path quality. In this section we show how these variables change the utility function and change the selection of neighboring nodes. The

Table 6.2 Average throughput for different average OFF periods of primary users

ν (sec)	SOP	DTCR	Optimum
3	0.211	0.921	0.931
30	0.816	0.925	0.931
60	0.919	0.928	0.931

variable $0 \leq \beta \leq 1$ is the knob that controls the significance of the amount of gain associated with relying on the spectrum measurement. Consider a node i with 5 neighbors. After sensing, it has the following maximum duration of channel availability of a spectrum for each of its neighbors

$$R_i = \begin{pmatrix} 0.33d^* & 0.5d^* & 0.66d^* & .88d^* & d^* \end{pmatrix},$$

where neighbor 5 with d^* has the maximum duration of channel availability to node i . In order to see the effect of β in the utility function, we kept all the parameters in equation 8.1 constant. First, we let $\eta = 1$ for all the neighbors, meaning we assumed the remainder of the path to the gateway is good for all of them. The variable $\gamma = 0.05$. As shown in the Figure 6.9, the utility corresponding to the fifth neighboring node is equal to one, and the utility of other neighbors decreases exponentially as β increases. The smaller the value of β , the less is the difference between the neighbors' utility. The parameter β could be chosen so that a node that does not necessarily have the maximum duration of channel availability is selected. As explained in the previous section, for some applications it is important to avoid paths that have high fluctuation of bandwidth variation. The parameter $0 \leq \gamma \leq 1$ controls the sensitivity of a node to this variation.

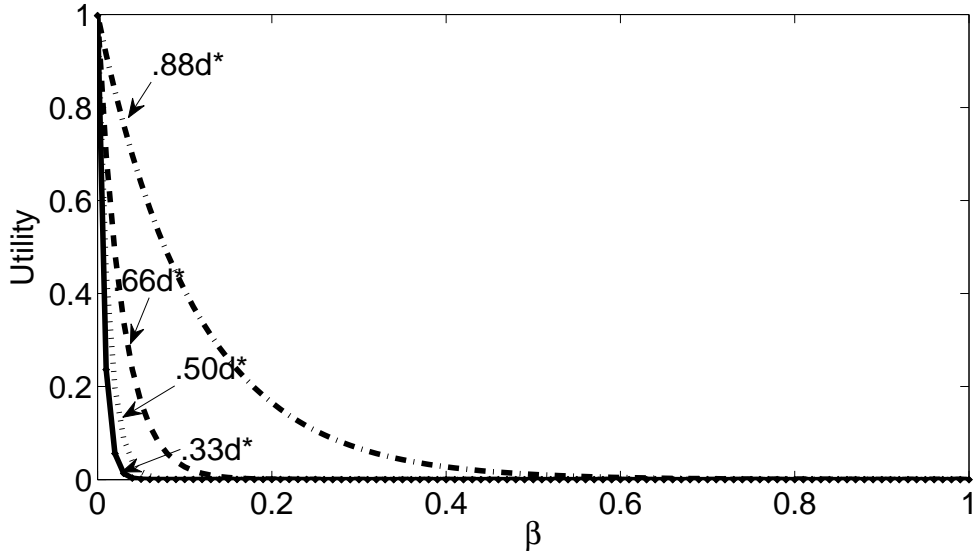


Figure 6.9 Utility on the states of 5 neighboring nodes, with different β values.

According to Figure 6.10, when γ increases, the nodes' utility assumes a larger distance from each other. After some point, there is no increase in utility. By choosing $\gamma = 0.2$, a designer can avoid choosing nodes with duration of channel availability below 0.88 of maximum channel availability duration. Hence, a node is sensitive to channel variations. The parameter η_j is very important in

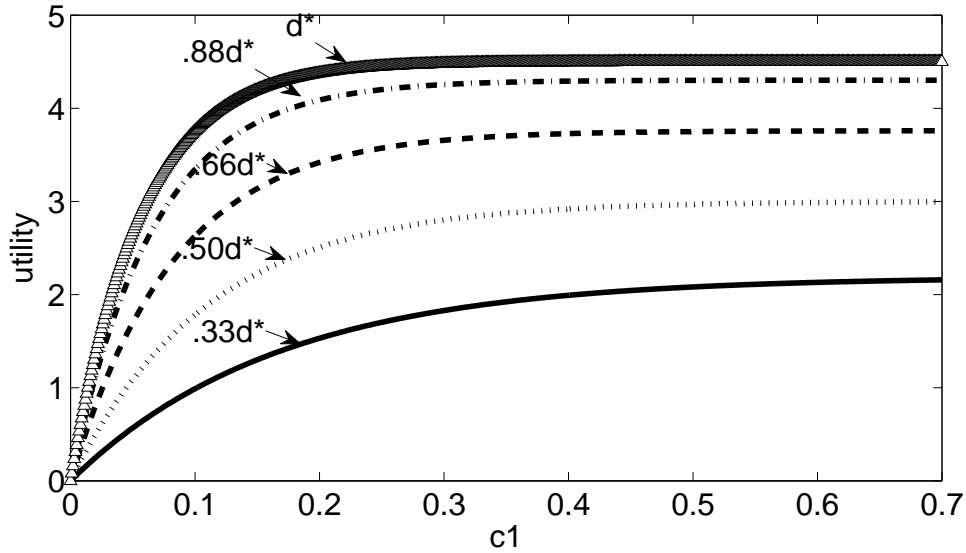


Figure 6.10 Utility on the states of 5 neighboring nodes, with different γ values.

choosing a stable end to end path. This variable could be evaluated according to any metric that the

designers feel suitable and affordable such as delay. We used relative queue remaining capacities of a neighbor node j . Therefore $0 \leq \eta \leq 1$. We assigned the following values for each of the neighbors, $\eta_1 = 1, \eta_2 = 0.8, \eta_3 = 0.6, \eta_4 = 0.4, \eta_5 = 0.2$. Therefore, the first neighboring node is on a very good path to the gateway. However, note that from R_i record, this neighbor channel's stability to node i is very low. On the other hand, the fifth neighbor that has a high channel stability to node i , is not on a stable path to the gateway. We choose these controversial values for parameter η on purpose to show how all of the above parameters come into play to aid node i to choose a good neighbor. We set $\beta = 0.05, \gamma = 0.2$. The utilities are shown in Figure 6.11. In this scenario, the fourth neighboring node has the highest utility. This neighbor is connected to node i and the gateway on a fairly stable path.

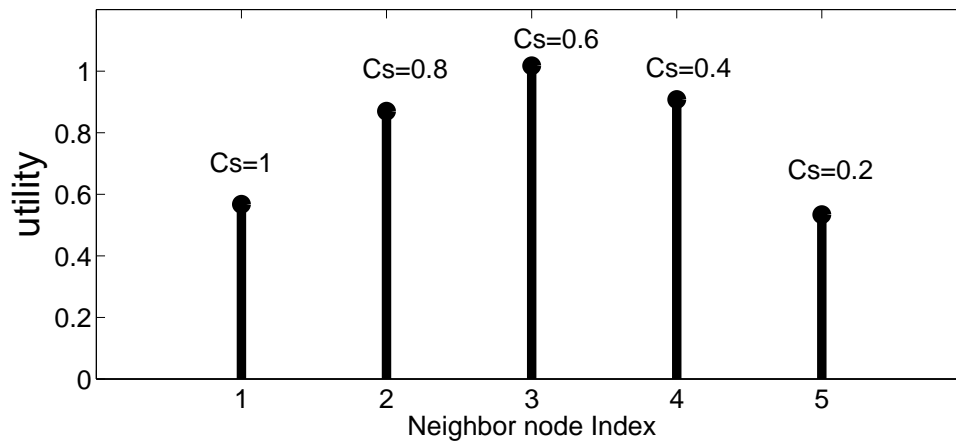


Figure 6.11 Utility on the states of 5 neighboring nodes, with different η values.

6.4 Summary

We presented a decision theory framework to analyze the problem of routing in a cognitive radio network operating in a highly dynamic environment. We modeled a node's decision among its candidate neighbors into a decision tree, and utilized a novel utility function to include the effect of

spectrum availability, bandwidth fluctuation and path uncertainties in a node decision making. The best candidate is chosen by analyzing the tree with backward induction and eliminating the choices that might decrease the node gain when selected with uncertainty. The Decision Tree Cognitive Routing scheme (DTCR) leads the node to choose the best candidate under high environmental variations.

Chapter 7

Decision Tree Modeling for Video Routing in Cognitive Radio Mesh Networks

In this chapter, we translate video routing in a dynamic cognitive radio network into a decision theory problem. Then terminal analysis backward induction that was used in previous chapter is used again to produce our routing scheme that improves the peak signal-to-noise ratio of the received video. In the proposed Video aware Cognitive Routing strategy (VCR), the sample and posterior distributions of the decision theory based scheme of previous chapter are tailored to explain the status of channels and nodes in supporting video frame quality of service, more specifically, the priority of I B and P video frames.

Similar to DTCR, in VCR the two probability laws, prior and posterior distributions are used. A prior distribution governs and explains the natural status of the states (neighboring nodes) unknown to the decision maker (sender). A posterior distribution gives the sender understandings of unknown states after performing an experiment that gives partial additional information on the status of unknown states. The nodes use their sensing data to predict future state of channels and reliability of the candidate nodes. New coding schemes such as H.264 [61] slices the video into I, P and B frames, with high to low priority of reconstructing the video at the receiver. The VCR selection takes into account the video frames priorities and their required bandwidth. More specifically, the VCR is a per-hop routing scheme, in which the next node decision process is modeled into a

decision tree. Each branch of the tree models a different scenario that might be shaped by spectrum availability uncertainties in dynamic cognitive radio networks. Nodes sense the surrounding channels and construct a record of channel availability durations. The bandwidth requirement of different frames in a group of video pictures (GOP) is taken into considerations, and nodes classify their channels records accordingly. Then, sampling probabilities are constructed using the ArgMax probability distribution introduced in Chapter that points to the node with the maximum duration of channel availability in its records. Using the sampling probabilities, we construct posterior probability distributions. The posterior distributions provide partial information on the uncertainty in the existence of channels that can support the required video quality of service. Using this approach, nodes undertake spectrum and node selection simultaneously. The utility function similar to previous chapter is used to adjust the gain by changing the significance of parameters associated with spectrum stability, node reliability and bandwidth variability. We use backward induction to analyze the decision tree and find a decision road map for the nodes to select their next hop neighbor in response to changes in the environment

In summary the contribution of this chapter is as follows:

- Using a decision theory framework, we develop a video aware cognitive routing scheme (VCR) to model and analyze the problem of downlink routing of video packets in a dynamic CRN.
- We construct appropriate sample and posterior distributions to explain the status of channels and nodes in supporting video frames quality of service.

We compare the performance of VCR with OSDRP [33] in a cognitive radio mesh network that operates in a city downtown. A video file is transferred from a server to a client. Our simulation results show that VCR is more successful in maintaining an acceptable Peak Signal-to-Noise Ratio

(PSNR) than OSDRP as the arrival rate of primary users increases. In addition the reconstructed video is played back successfully at the receiver when VCR is used. However, due to loss of frames in OSDRP, the decoder is not able to reconstruct the entire video at the receiver.

The organization of this chapter is as follows. In Section 7.1, we show how DTCR decision theory framework is modified to generate the VCR scheme. In Sections 7.2 we elaborate on the VCR complexity. Section 7.3 presents the details of implementation and simulation results.

7.1 Decision Theory Framework of VCR

We consider a cognitive radio client in a multi-hop mesh topology network that is downloading high definition video from a server. The network is located in a city downtown, where activities of primary users is highly dynamic and unpredictable. All the nodes in the network have a cognitive radio transceiver. They also have an extra interface dedicated to a control channel. The control channel is only used for transferring control messages between the nodes. The video frames are transported hop by hop from the server to the client. Figure 7.1 shows a simple topology. In this section, this topology is used to explain the steps of our per-hop routing strategy. However, we show in Section 7.3 that the scheme is indeed applicable to larger size ad-hoc mesh networks. For simplicity, nodes that are located within the same number of hops from the server are grouped into one layer. We refer to a node i in a layer l as $i[l]$, $i = 1, 2, \dots, M$, where M is random and represents the total number of nodes in the network. A node in a layer l can choose any node in the lower layer $l + 1$ other than the nodes in its own layer who are authorized to send packets to the receiver. The client broadcasts its layer index in a video request packet, when a neighbor receives the request, it authorizes itself for that particular destination and informs its neighbors of its authorization by broadcasting the received video packet. Therefore via a back

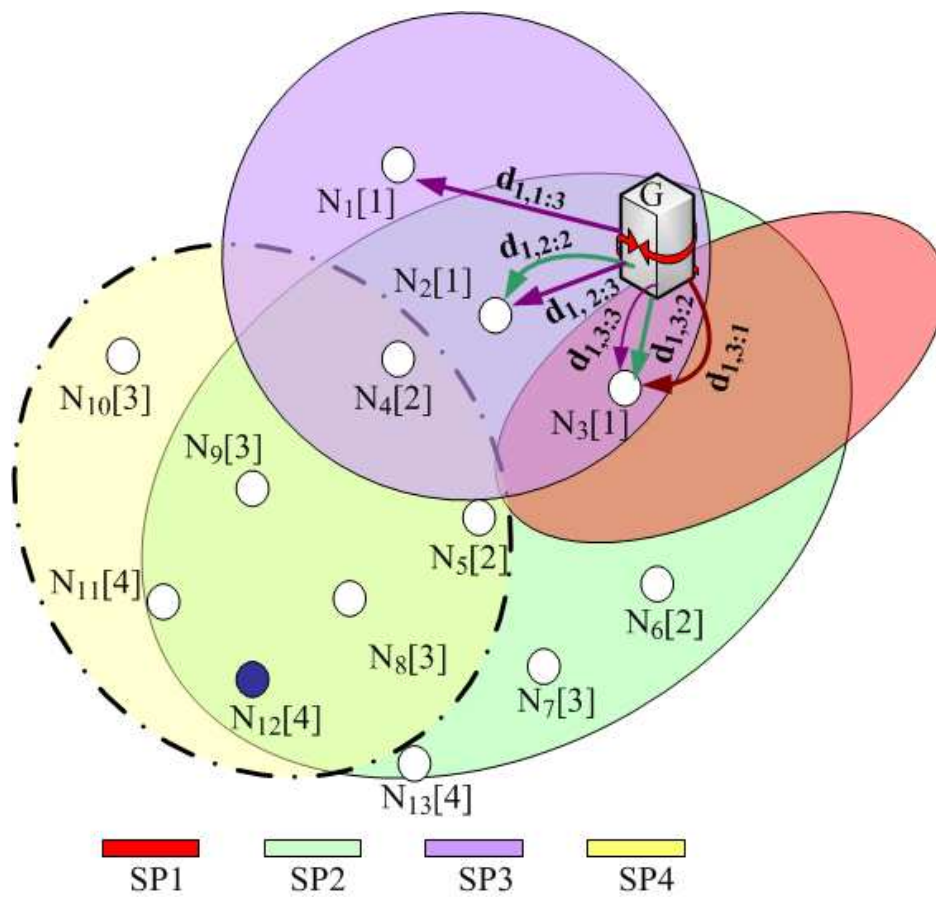


Figure 7.1 A simple downlink mesh network topology within a city with its node diagram

pressure approach, all the nodes are notified of their authorized neighbors. In addition, when a node handshakes with its neighbor it receives the neighbor's layer index. The layer index helps to avoid count to infinity problem.

Due to the nature of a cognitive radio network, available channels at each node have diversity in their bandwidth and duration of availability. Channels are available from a spectrum band when the primary user of that band is absent. Nodes access and share the available channels with OFDMA/NC medium access technique.

We view the selection of the best candidate among the neighbors of a sender node as a decision problem. Considering the uncertainties involved due to the arrival of primary users in cognitive radio networks, it is desirable to choose a neighbor that is most reliable in receiving video packets and forwarding them to the next node; and ultimately to the destination. The notations, we use in this chapter are that used in in Table 6.1. Lets assume that node 12[4] in Figure 7.1 is the client, and is downloading a video from the server (0[0]). Based on the spectrum coverage, and radio range of the gateway node, this node has 3 intermediate neighbors: 1[1], 2[1] and 3[1]. Node 0[0] chooses one of its neighbors. Due to the nodes mobility and variation in transmission range, each neighbor has a random number of neighbors N_i . In terminology of decision theory [16], the set of possible states (choices) available to the decision maker is represented by $\mathcal{S} = \{s_1, s_2, \dots\}$. The node 0[0] is the decision maker. The states unknown to the decision maker are the intermediate neighboring nodes, $s_1 = 1[1]$, $s_2 = 2[1]$ and $s_3 = 3[1]$. Therefore, $\mathcal{S} = \{s_1, s_2, s_3\}$. There is also a set of actions that the decision maker can take, represented by $\mathcal{A} = \{a_1, \dots, a_{N_i}\}$; a_ν is the act of choosing a state s_ν to visit. According to our example, we have three acts, a_1, a_2, a_3 ; a_ν corresponds to choosing a neighbor s_ν $\nu = 1, 2, 3$.

7.1.1 Initial Learning Phase

In this phase the sender gathers information from their neighbors and their surrounding spectral measurements to construct the decision tree as explained in Section 2.5. The node $0[0]$, sits at the root of the tree and the states are at the ending branches of the tree. Now similar to the uplink routing explained in previous chapter, the decision maker can perform an experiment to obtain additional information in support of an act. Performing an experiment e is not obligatory and the node may go for e_0 which means no experiment. Performing an experiment in decision theory means that the decision maker is willing to give some cost in exchange of gaining partial information about the status of the unknown states. The experiment e is collecting and reading a history of primary users' activities on its surrounding channels, then measuring the maximum duration of channels availability ${}_0z_j$ in spectrum bands between node $0[0]$ and neighbor j . Many previous studies in routing also rely on past measurements on the activities of primary users to find the most stable path [33, 60].

7.1.1.1 Local Spectral Bandwidth Observations

We assume that there are $K_{i,j}$ spectrum bands available between nodes i and j . Each spectrum band c has K_C number of channels. Node $i[l]$ handshakes with its neighbor node j , $j = 1, 2, \dots, N_i$, and receives the signal-to-noise ratio gain (SNR_g) of every channel $k_{i,j}$ in spectrum band c , $k_{i,j} = 1, \dots, K_C$, that connects node $i[l]$ to the node $j[l + 1]$. It then evaluates the period of occupancy of each channel occupied bandwidth of the channel $k_{i,j}$, denoted by $Y_{k_{i,j}}$, based on equation 6.2. Let us denote the duration that the primary users do not use the channel $k_{i,j}$ by $X_{k_{i,j}}$. Then the duration of channel availability is $T_{k_{i,j}} = X_{k_{i,j}} - Y_{k_{i,j}}$. The video is compressed using H.264 codec standard [61]. After compression, a group of pictures (GOP)

consists of three types of frames: Intra-coded picture or I frame, Predictive picture or P frame and Bi-predictive picture or B frame. An I frame is the most important frame. It has the main static picture of a GOP, meaning if an I frame is lost, the scene of the video corresponding to that particular GOP will not be constructed at the receiver. P frames are also important to provide reasonable video quality. On the other hand, B frames could be predicted if I and P frames are available. This type of video compression will provide a tolerance on packet loss as long as they are mostly B frames. Therefore, the I frames are larger in size and receive high priority. In order to make our decision scheme sensitive to the priority of I and P frames, we classify the $T_{k_{i,j}}$ into two groups of $I_{k_{i,j}}$ and $P_{k_{i,j}}$, as follows:

$$\begin{aligned} I_{k_{i,j}} &= T_{k_{i,j}} \text{ if } T_{k_{i,j}} > T_I, \text{ for } k_{i,j} = \{1, \dots, K_C\} \\ P_{k_{i,j}} &= T_{k_{i,j}} \text{ if } T_I > T_{k_{i,j}} > T_P, \text{ for } k_{i,j} = \{1, \dots, K_C\}, \end{aligned}$$

where T_I and T_P are the time durations required for sending I and P frames across the channel $k_{i,j}$ respectively. $\mathcal{I}_{i,j} = \{k_{i,j}; T_{k_{i,j}} > T_I\}$ and $\mathcal{P}_{i,j} = \{k_{i,j}; T_I > T_{k_{i,j}} > T_P\}$.

Finally, node i stores the maximum observed duration of channel availability in the spectrum bands between itself and each of its neighboring node, into a vector R_i :

$$R_i = \begin{pmatrix} {}_i z_1 & {}_i z_2 & \cdots & {}_i z_{N_i} \end{pmatrix}.$$

The variable ${}_i z_j = \max_{k_{i,j} \in \mathcal{I}_{i,j}} I_{k_{i,j}} + \max_{k_{i,j} \in \mathcal{P}_{i,j}} P_{k_{i,j}}$ shows the maximum observed duration of channel availability in the spectrums between node i and j . The set of possible samples is represented by $\mathcal{Z} = \{{}_i z_1, {}_i z_2, \dots\}$. The variable ${}_i z_j$ is a sample observation in favor of node j .

Therefore, node 0[0] in our simple mesh network, Figure 7.1, constructs the following record.

$$R_0 = \begin{pmatrix} 0z_1 & 0z_2 & 0z_3 \end{pmatrix}.$$

The record vector R_i is used to construct the sample and the posterior distribution for the maximum spectral channel availability durations similar to the previous chapter. Refer to section 6.1.2 and section 6.6 to see how these distributions are constructed from R_i records.

Similar to previous chapter, We define the following utility function. for the experiment e

$$u_i(e, j^*, a, j) = c_j [1 - e^{(-\gamma_i z_j^*)}] [v(a, a_j^*) \mu(a, j)]. \quad (7.1)$$

For no experiment e_0

$$u_i(e_0, a, j) = c_j \mu(a, j), \quad (7.2)$$

where c_j is a constant that reflects the transferring quality of node j specified by the remaining queue capacity of node j . The γ is the controlling factor to quantify the amount of channel availability variation. The function $V(a, a_j^*)$ reflects the spectrum band quality, defined in formula 7.3.

$$\mu(a, j) = \begin{cases} 1 & \text{if } a = j, \text{ when } j \text{ is the true state,} \\ 0 & \text{if } a \neq j, \text{ when } j \text{ is the true state.} \end{cases}$$

Figure 7.2 shows some utilities on the node 0 decision tree.

When observing the channels in a spectrum and measuring the maximum duration of their availability without any interruption from primary users, it might be more beneficial to a node to use a channel from a specific spectrum that has less availability duration but is connected to a node that might be on a better path. The gain associated to choosing a node based on its spectrum band

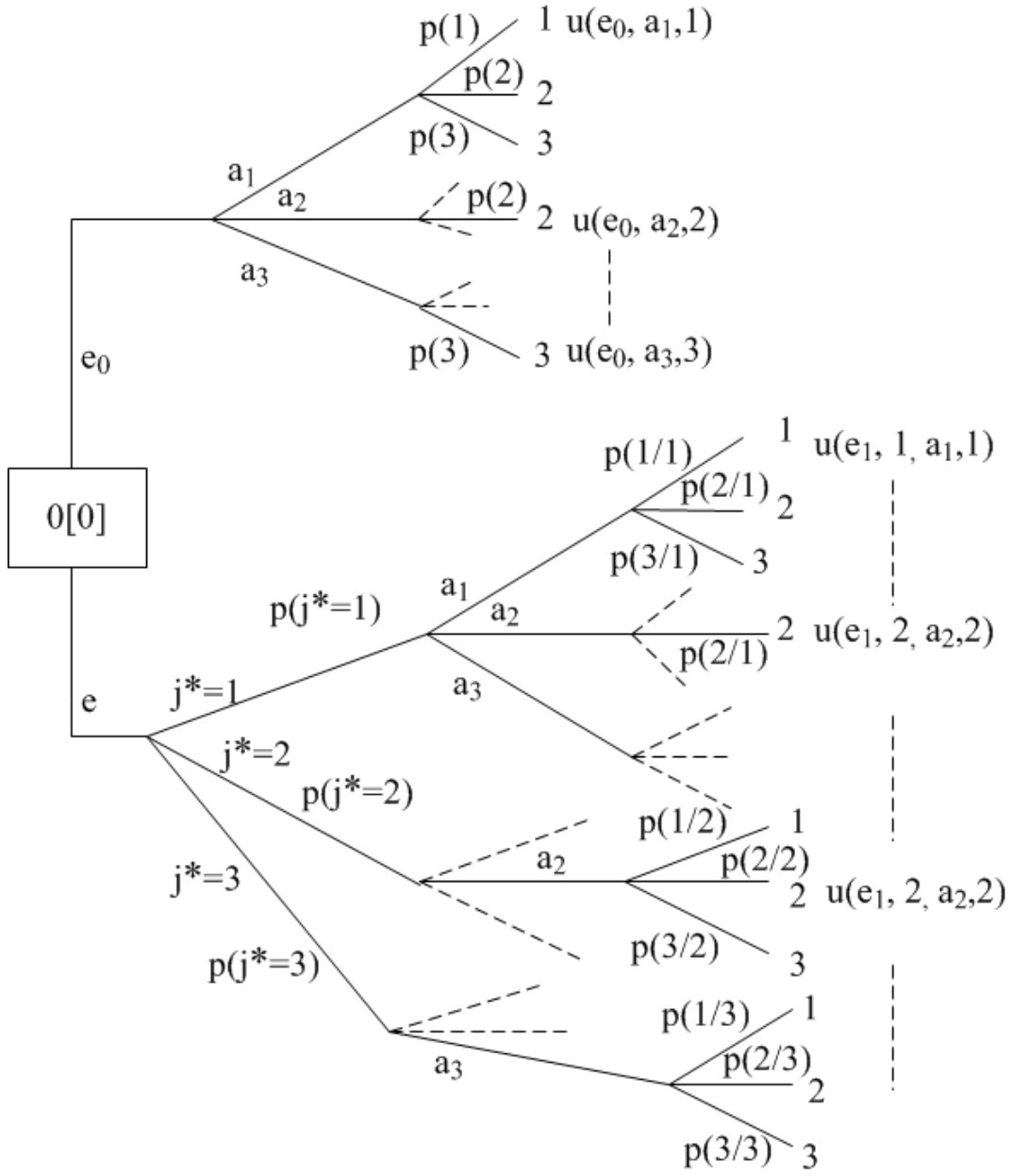


Figure 7.2 Node 0 decision tree with some utilities

quality is quantified with the following formula.

$$V(a, a_j^*) = b_1 e^{-b_2 [A_e(a) - A_e(a_j^*)]^2} \quad (7.3)$$

where $A_e(a)$ is the gain associated with choosing the right act a and $A_e(a_j^*)$ is the gain of choosing

the act a_j^* following the sample observation j^* . For example, if the measurement of the maximum duration of channel availability of spectrums are as follows,

$$R_1 = \begin{pmatrix} 12 & 8 & 18 \end{pmatrix},$$

then the $A_e(a) = 18$, $A_e(a_1) = 12$, $A_e(a_2) = 8$, $A_e(a_3) = 18$. Therefore, sample $0z_3$, leading to choose node 3[1] in our scenario, provides the maximum gain. The parameters b_1 and b_2 are the knobs that control the significance of the amount of gain associated with relying on the spectrum measurement. If b_2 is small, a node may be chosen that does not necessary have the highest duration of spectrum availability. In other words b_1 and b_2 provide the network designers with an error tolerance factor in spectral measurement.

Some applications in CR networks suffer from high fluctuation of bandwidth availability due to fluctuation in the channels' availability. The variable ${}_i z_j^*$ is a measure of the maximum duration of channels availability between i and j obtained from the experiment. When ${}_i z_j^*$ is high the utility is large. The variable γ is the controlling factor to quantify the amount of variation. Depending on the sensitivity of the application on the bandwidth fluctuation, γ is selected. For example, when γ is around 0.5, a small difference in the duration of channel availability would provide a significantly higher gain and the node is encouraged to choose the node with highest duration of availability.

As mentioned previously, the environmental dynamics of the cognitive radio network might change and the node might choose a neighbor that was not the most appropriate node in routing. The indicator function μ is chosen to model the gain/loss for such scenario. Note that based on μ , we assume total loss when a wrong node is selected to transfer packets. A wrong node would not necessarily give a total loss but may be able to transfer some packets based on its queue capacity. An interesting future direction is to model μ according to nodes queue length.

It is essential that the node considers the quality of the remainder of the path to the gateway when choosing its intermediate neighbor. The variable c_s reflects this metric. Some researchers use the average backlogged queue length [14] to quantify the quality of the path. For our utility function we use the remaining queue capacity of node j to quantify the value of c_s .

After the construction of an appropriate decision tree for our routing problem, the optimum strategy (course of action) is specified by the backward induction terminal analysis introduced in section 6.2

The backward induction procedure for our simple mesh network is depicted in Figure 7.3, The course of action in this example is through experiment e . Then for $j^* = 1$ choose $j = 3$, for $j^* = 2$, choose $j = 1$, and for $j^* = 3$, choose $j = 3$.

7.2 VCR Complexity

The run time complexity of the proposed scheme (VCR), is $\Theta(n)$, where $n = N_i^2$ corresponds to the size of the matrix for the construction of the posteriori distribution. we recall that N_i is the maximum number of neighbors of node i at time t . Since the VCR is a decentralized algorithm, the number of accessible neighbors of a node is bounded and limited. Therefore, VCR will converge quickly.

In order to have an estimate of the sample size m required for the construction of posterior probability distribution $P_i(j|j^*)$. We use the law of the iterated algorithm proposed by Kolmogorov, in [56]. The upper and lower bound on the rate of convergence of the estimator of a distribution to

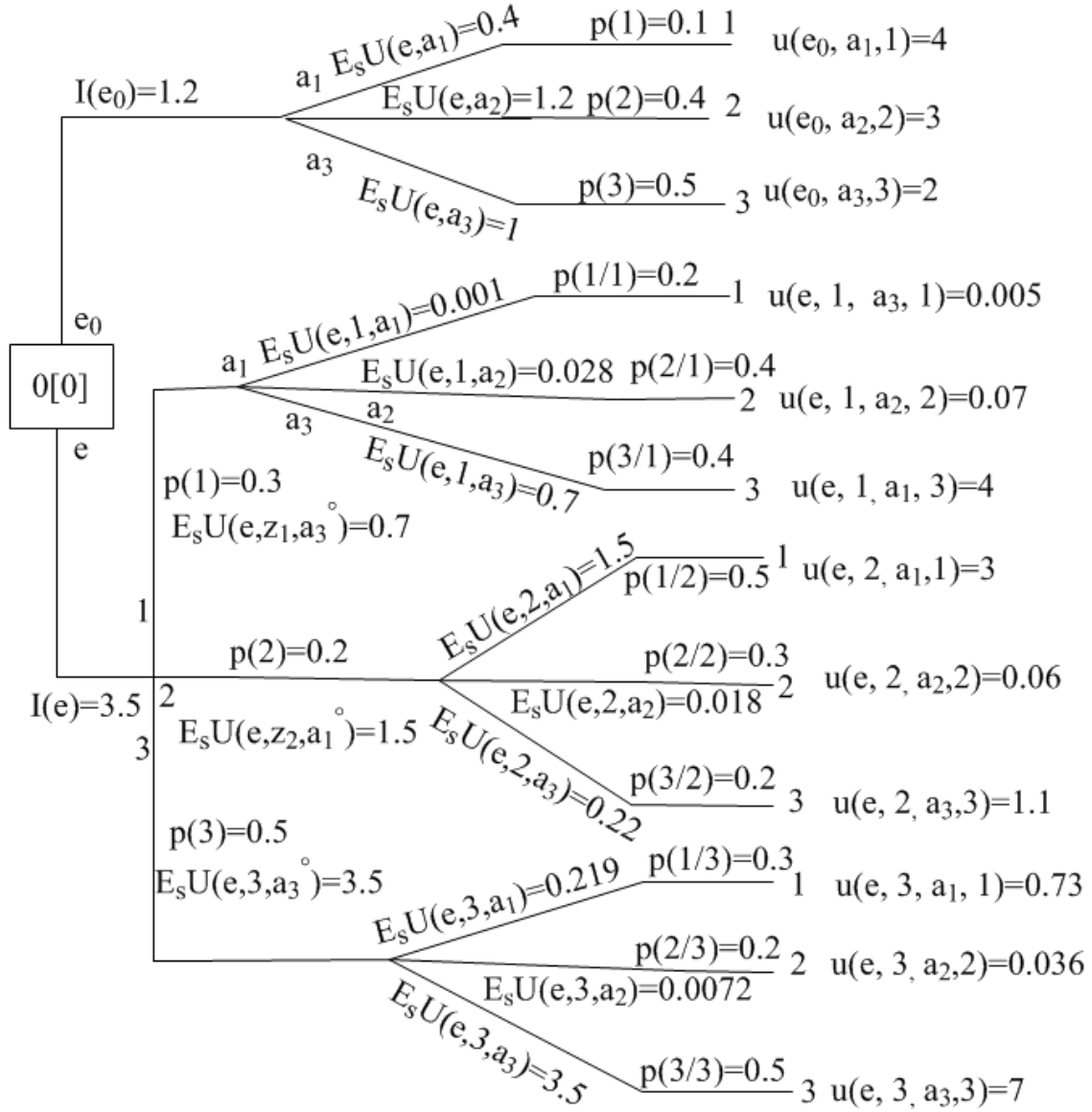


Figure 7.3 Node 0 decision tree with backward induction procedure

its true value are as follows

$$\limsup_{m \rightarrow \infty} \frac{\sqrt{m} \|\hat{P}_m - P\|}{\sqrt{2 \ln \ln m}} \leq 1/2$$

$$\liminf_{m \rightarrow \infty} \sqrt{2m \ln \ln m} \|\hat{P}_m - P\| = \pi/2$$

From the above, the upper bound on the error of the estimator based on the sample size m , follows

that for large m :

$$\|\hat{P}_m - P\| < \frac{\sqrt{\ln \ln m}}{\sqrt{2m}}. \quad (7.4)$$

Therefore, for $m = 100$, the error is about 0.15; as m increases the error converges exponentially to zero. By selecting $m = 200$, the error is 0.004. If we assume that the network installed in an area, just started to operate, then the first 150 msec of the operation time should be dedicated to collecting about 150 samples.

We discarded the memory of the node after taking and using a sample of 150 matrices to minimize memory usage.

7.3 Simulation

Our topology is similar to Figure 7.1. The number of accessible nodes N_i varies depending on the radio signal strength. A random value is assigned for the radial distance of node i from node j . If node j is within the radio transmission range of node i , it is considered accessible by node i . In our simulation model we have 5 spectrum bands. The range of their corresponding bandwidth changes from 6Mb/sec (could correspond to FM radio band) to 144Mb/sec (similar to a TV channel). Note that a spectrum band depending on its type could have different number of channels. The bandwidth of each spectrum is divided equally among its channels. We used the JSVM software tools to generate realtime traffic. A YUV video file with 176x144 pixels per inch (ppi) spatial resolution is encoded and the stream file is extracted. The stream file has I, P and B packets with high to low frame length respectively. In addition, network nodes also generate traffic packets with 512 bytes size, to demonstrate a real life scenario where there exists other traffic activities on the network. The packets arrival rate is based on a lognormal distribution with mean ν and standard deviation σ , based on the measurement study [50]. We used μ as 0.8, 0.2, 0.5 and 0.5 variance to model a heavy,

moderate and light occupancy of users on channels. The video file is sent from the server to the client which is located in the outer layer. We compared our method with OSDRP [33] designed for

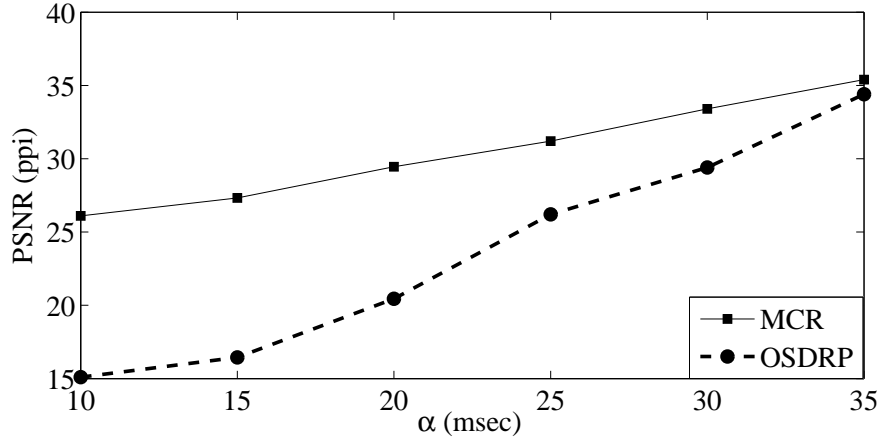


Figure 7.4 Mean peak-signal-to-noise ratio for different α

a dynamic environment. In OSDRP protocol, the end to end routes are found based the deterministic strategy of the DSR protocol, and are prioritized according to the route lifetime. Route lifetime is based on the channel availabilities as well as channel switching and queuing delays. In addition, in order to support QoS, it controls the transmission power and selects the nearest forwarding SUs to the SU destination node.

Figure 7.4, shows the robustness of our scheme to the primary users' arrival rate. A network with 30 nodes is chosen scattered around in 1000x1000sqm field. The measurement study [54] suggests that the primary user's traffic follows a Semi-Markov process with OFF/ON periods following an exponential distribution. Therefore, the primary users' idle period is an exponential distribution with mean α . As α gets larger, the channels are interrupted less frequently by primary users.

As the mean idle period of primary users decreases, the PSNR tends to degrade for OSDRP. In OSDRP the routing tables are not updated frequently enough and the repetition of calling the

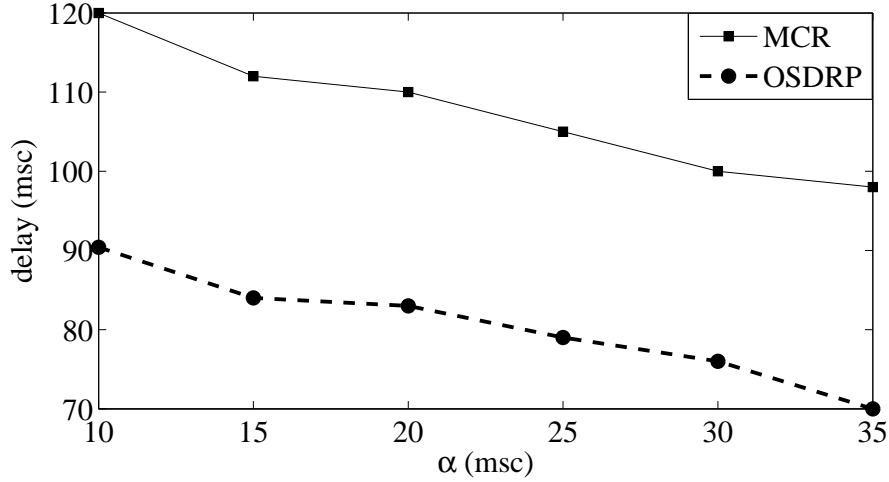


Figure 7.5 End-to-end delay for different values of α

route request mechanism results in transmission delay and packet loss. VCR makes its decision considering the uncertainty of primary users' arrival. In addition, the links are chosen that can support the required transmission duration of I and P frames. As a result the video quality is acceptable even when the primary users' arrival is high. There are many controlling parameters such as b_1, b_2, c_2 , in the utility function of VCR that can be adjusted to achieve better performance. One interesting future direction is to adjust those parameters adaptively according to the video quality variations at the receiver. We used $b_1=5, b_2=1$ and $c_2=0.5$ in our simulation.

Figure 7.5 shows the end-to-end delay of video frames for different mean idle periods of primary users. We see that the OSDRP achieves lower delay. However, based on Figure 7.7, the relative loss frequency of I and P frames are higher in OSDRP than those of VCR. The video quality degrades substantially with the loss of I and P frames. We see that VCR is losing the B frames more than the other frames. Hence it is able to provide better video quality. The initial learning phase of VCR also adds to its end-to-end delay but VCR fast decision making based on the stored optimum strategy compensates for the delay. Ultimately, the video is received with a high quality at the receiver. The relative loss frequency is calculated by dividing the total number of loss of

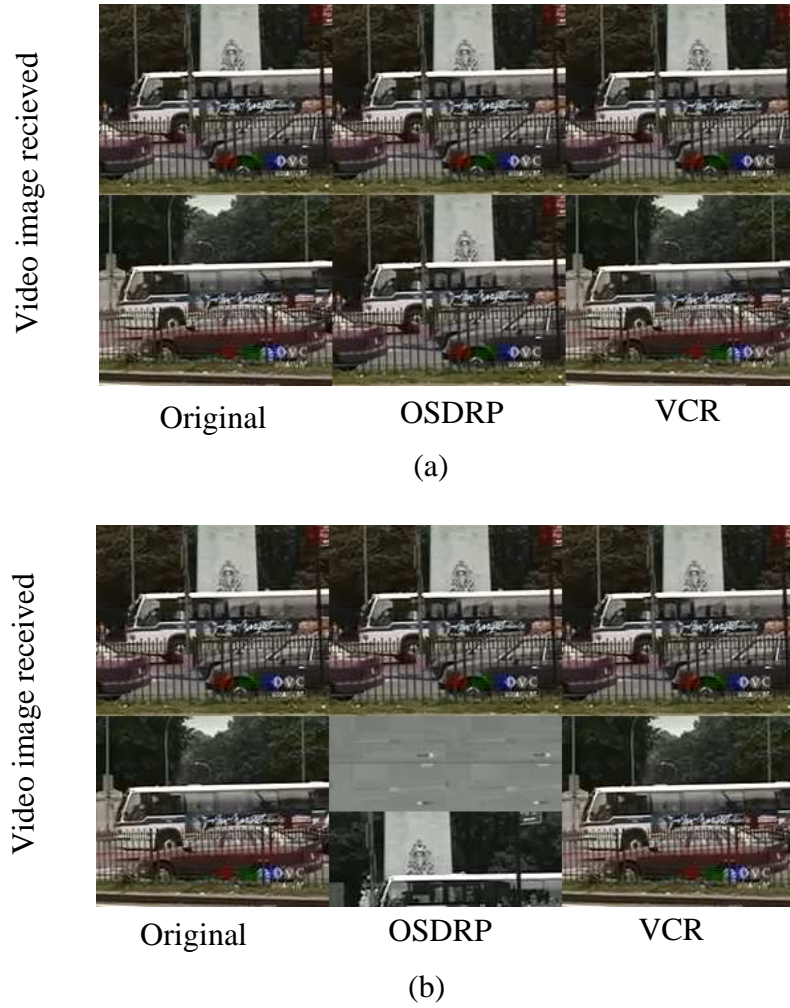
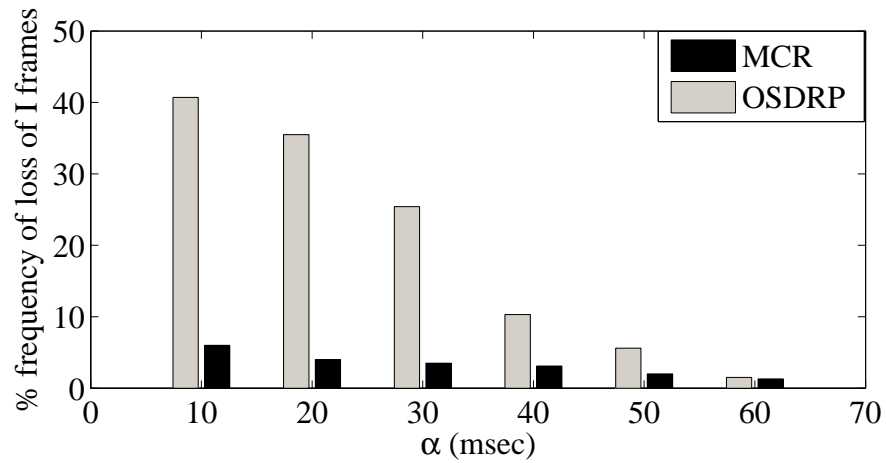


Figure 7.6 Reconstructed Video frames (a) $\alpha=20\text{msec}$, (b) $\alpha=30\text{msec}$

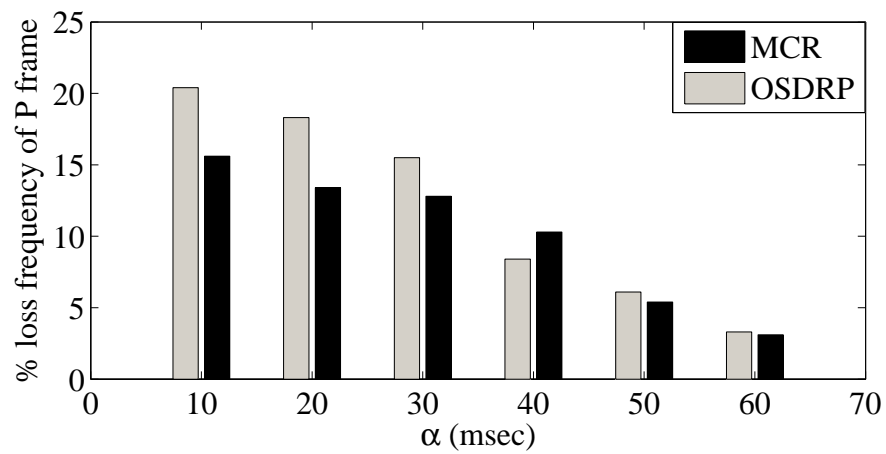
each particular frame over the total number of that frame in the original YUV file.

Figure 7.6, shows the decoded video at the receiver for $\alpha=20\text{ msec}$, and $\alpha=30\text{ msec}$. As shown in Figure 7.6a, the video player is unable to decode the video beyond a received image and freezes. When $\alpha=30\text{ msec}$, the video is viewable but its quality degrades in OSDRP in comparison to MCR.

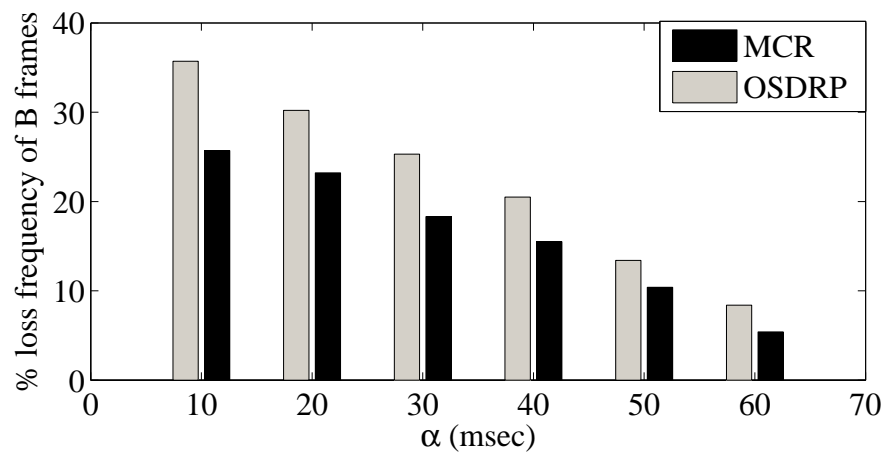
Our simulation results show that it is beneficial to use nondeterministic system theories such as decision theory framework to cope with agile variations is spectrum diversity and availability of dynamic cognitive radio networks.



(a)



(b)



(c)

Figure 7.7 The relative loss frequency of I, P and B frames

7.4 Summary

We used a decision theory framework to analyze the problem of downlink video routing in a cognitive radio network operating in a highly dynamic environment. The video cognitive routing (VCR) strategy models a node's decision among its candidate neighbors into a decision tree. VCR utilizes a posterior distribution that provides information on the links durations uncertainty and ultimately the suitability of a neighbor node by taking the priorities of video frames into consideration. The best candidate is chosen by analyzing the tree with backward induction and eliminating the choices that might decrease the sender's gain. The VCR guides the node to choose the best candidate under high environmental variations. Our results show that VCR is successful to maintain the video quality even when the primary users arrival rate is extremely high.

Chapter 8

Summary and future work

8.1 Summary

We investigated the problem of routing in cognitive radio networks. We proposed two new probability distributions called ArgMax and ArgMin that could be used in probabilistic protocols. The ArgMax probability distribution locates the maximum random variable among a set of random variables, while the ArgMin locates the minimum random variable. The ArgMax probability distribution is shown to outperform odds-on-mean probability distribution which is used frequently in many applications. The ArgMin probability distribution has a variety of applications and is shown to be useful in achieving a lower bound on the network's minimum spectral capacity. Using these two probability distribution, we introduced an interesting measure called *primary weight measure*, which indicated the frequency and the nature of the distribution of primaries around a particular node. A low value of the primary weight measure metric indicated uniform and frequent primary users interruptions on the channels surrounding a node. With this information MAC and routing decisions are taken more efficiently. We developed a stochastic based routing called Primary Spread Aware Routing Protocol (PSARP). On a cognitive-based NS2 network simulator, we compared the performance of PSARP with two previously developed routing protocols for dynamic environment. We also developed a Cognitive Stochastic Routing (CSR) protocol based on the PSARP stochastic framework that uses backlogged queue capacity instead of PWM. Our results

show higher throughput in PSARP and CSR, which indicate the advantage of stochastic-based routing in a dynamic environment. In addition, PSARP with its PWM measure is more successful in choosing the best path due to the correct identification of the primary users' distribution, and performs substantially better than CSR at high rates.

We used the decision theory concept and developed the decision tree cognitive routing scheme (DTCR) and extended it to VCR to support a downlink video transfer in a dynamic environment. We compared the performance of our DTCR strategy with the optimal strategy. In the optimal strategy, nodes had full knowledge of the future changes in the network parameters. In other words, no routing strategy performs better than the optimal strategy. We also compared our method with the local coordination based routing and spectrum assignment protocol [58] to measure the deviation of our scheme and a routing protocol designed for a dynamic environment from the optimum strategy. Our results show that our DTCR successfully treats the occurrence of uncertainty and performs close to the optimal scenario. The DTCR uses the posterior probability distribution to estimate the availability of a neighbor under uncertainty. The backward induction scheme helps a node to choose a neighbor that is more likely to be the correct candidate; it reduces the cost of choosing wrong candidates. Therefore, it operates substantially better than the local coordination based routing protocol; its performance is indeed near optimal at low and moderate sending rates. However, at high sending rates, it still outperforms the local coordination based routing. Our simulation results of evaluating the VCR also show that VCR is more successful in maintaining an acceptable Peak Signal-to-Noise Ratio (PSNR) as the arrival rate of primary users increases. In addition the reconstructed video is played back successfully at the receiver when VCR is used.

The strategies developed could be used in many future designs to accommodate different needs of network administrators. Using decision theory in cognitive radio networks opens the possibility to use unlimited decision theory tools in developing new controlling and monitoring schemes. One

can also simply look at the utility function defined in DTCR to adjust its parameter according to the designers requirements or network performance. In this chapter, we elaborate on some possible future directions.

8.2 Extensions and future works

8.2.1 Utility Function Adjustments

Recall that the DTCR uses a utility function as one of its decision making component. The utility function we used is defined in subsection 6.1.4 as follows:

$$u_i(e, j^*, a, j) = \eta_j [1 - e^{(-\gamma_i z_j^*)}] [v(a, a_j^*) \mu(a, j)]. \quad (8.1)$$

Note that in our modeling, we go for zero-one scenario, in the sense that wrong selection of the node is a total loss, i.e. zero utility. Thus, we let

$$\mu(a, j) = \begin{cases} 1 & \text{if } a = j, \text{ when } j \text{ is the true state,} \\ 0 & \text{if } a \neq j, \text{ when } j \text{ is the true state.} \end{cases}$$

However, the selection of a wrong node does not necessary mean a total loss because as long as the selected node does not have a full queue, it is still able to transfer some of the packets. One future direction is to model the parameter μ as a function of remaining queue capacity of the neighbor nodes. Therefore, we do not assume total loss by selecting a wrong node but some loss according to the transfer ability of the neighbor node.

The three control parameters β, γ, η exist that quantify the importance of local spectral mea-

surement, its variation, and path quality. Any of these parameters can be modeled as a function of changes in flow dynamics or the quality of service requirements of a particular flow. For instance, variable γ can be a function of required bandwidth of a certain flow to make the sensitivity of the DTCR strategy self adaptive to the requirement of a particular flow passing through a specific node.

Also, our utility function is concentrating on choosing a channel that has the least bandwidth variability and the most stability in dynamic environment. This function could be altered to consider the delay or Expected Transmission Time (ETT) of packets in applications that are delay sensitive. In addition, the utility function could take into account the transport level requirements or be replaced by the utility functions that are designed for congestion control schemes such as the ones described by Kunniyur et. al. in [62].

8.2.2 Primary Weight Measure in DTCR

The parameter η is the average queue capacity of the neighboring node. This metric provides a reliability measure over links located one hop further. However, the queue capacity variation decreases when the load increases. Hence, DTCR selection is blind to the behavioral pattern of primary users located one hop away from its intermediate neighbors at low and high rates. We proposed the PWM metric in Chapter that not only provides a measure on the reliability of non-intermediate links but indicating the distribution of primaries around a particular node. One interesting future direction is to design η not only based on the queue capacity but also the PWM measure. The $PWM[i, j]$ indicates the degree of nonuniform spread of primaries in channels between nodes i and j . For $PWM[i, j] \sim 0$, primaries are more spread uniformly, and consequently there be no privilege to any transitions distribution. For large values of $PWM[i, j]$ there is a cluster of channels at that node for which the presence of primaries is much less than the others and therefore choosing that

particular node provides a significantly stable path. This metric is highly informative about the reliability of the links surrounding a node. PWM could be used as one of the meters that is read by the cognitive engine of cognitive radios to indicate what knobs needs to be adjusted to avoid inefficient transmission. (We encourage the readers to refer to Chapter for the definition of knobs and meters).

8.2.3 More Decision Theory

It is also interesting to bring the advance concepts of decision theory into our decision theory modeling of cognitive radio networks to evaluate the behavior of these networks over time. For instance, recall that the optimal act will minimizes the expected loss or maximizes the expected gain; the later is $\max_e E_{p(z|e)} [\max_a [E_{p(s|z,e)} U(e, z, a, s)]]$, where $p(z|e)$ is the marginal sample distribution for the e and $p(s|z, e)$ is the posterior distribution, $p(s) \sim p(s|z_o, e_o)$ stands for the prior distribution, e_o (no experiment), z_o (no observation). The quantity $E_{p(s)} [\max_a U(e_o, z_o, a, s)] - \max_a E_{p(s)} U(e_o, z_o, a, s)$ is referred to as EVPI, the expected value for perfect information. It is simply the expected opportunity lost by taking the act that maximizes the expected utility. This quantity helps a cognitive node to consider the opportunity loss. If this quantity is not high, it takes the act that is more cost efficient. The cost could be the node energy, storage or delay. In the broader perspective, the EVPI could be used to analyze the end-to-end cost of the system.

We encourage the readers to look at further concepts of decision theory and see how many of them could be incorporated in system evaluation, design and modeling in cognitive radio networks.

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