SPECTRUM-AWARE ROUTING IN COGNITIVE AD HOC SENSOR NETWORKS

DISSERTATION

for the Degree of

DOCTOR OF PHILOSOPHY
(Electrical Engineering)

HUMA GHAFOOR

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Huma Ghafoor

supervised by

Professor Insoo Koo

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Approved by Supervisory Committee:

Prof. Myung-Kyun Kim, Chair

Prof. Insoo Koo, Supervisor

Prof. Vladimir V. Shakhov

Prof. Hyung-Yun Kong

Prof. Youngtae Noh

Department of Electrical and Computer Engineering
University of Ulsan, South Korea

Date: May, 2018

VITA

Huma Ghafoor was born in Multan, Pakistan, in 1985. She received the B.Sc. degree in Electronics Engineering from the NFC Institute of Engineering and Technology, Multan, Pakistan in 2009, and the M.S. degree in Communication Systems Engineering from the School of Electrical Engineering and Computer Science (SEECS), NUST, Islamabad, Pakistan in 2012. Since September 2013, she has been involved in the Doctoral Program at the University of Ulsan (UOU), South Korea under the guidance of Professor Insoo Koo. Her current research interests include vehicular ad hoc networks, underwater sensor networks, and software-defined networking with a focus on cognitive networking protocols.

Dedicated to my dearest parents

for their support and care

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ABSTRACT

Spectrum-Aware Routing in Cognitive Ad Hoc Sensor Networks

by

Huma Ghafoor

Supervisor: Prof. Insoo Koo

Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy (Electrical Engineering)

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The earth, a watery place because of a higher percentage of water than the land, has several communication technologies that help to improve our living standards. Observing our planet in this regard, there exist different living organisms on the land surface, the sea surface and in the ocean which communicate daily with their species using different spectrum. Along with these living things, there are several non-living things with some similar characteristics of living things on the earth e.g., vehicles that need to be fed with petrol, sensors that have ability to adapt according to the environment and need energy to continue existing, machines or robots that can move, and many more, which utilize the same spectrum for communications. Nowadays, we are more than 60% dependent on these non-living things to make rapid advancements in inter-networking. Inter-networking is a connecting phenomenon that requires a routing protocol to transfer the data packets between different networks by using gateways. Routing is a process that helps sensor nodes to establish a stable link to forward a message to its destination. Hence, to improve communications among different kinds of communicating devices on the land, the sea surface,

and in the ocean, three types of sensor networks: terrestrial, maritime, and underwater are designed to deal with various applications, respectively.

As we are exposed to a plethora of mobile applications over the past few years, our living standards are becoming increasingly the part of smart networking. Among various kinds of other systems that are essential to improve our living standards all over the world, the intelligent transportation system is the one that overcomes serious issues due to road accidents. Millions of deaths are caused by road accidents. Therefore, in this thesis, we consider vehicular ad hoc networks as the terrestrial networks. Vehicular ad hoc network is a promising mean for safe driving by enabling cooperation among vehicles. And when it comes to safe and stable communications at the sea surface, maritime ad hoc networks are the ones that play an essential role in providing a variety of safety to users aboard. Similarly, communications in the ocean have also been attracting significant interests to deal with various applications for underwater networks. Hence, in this thesis, we consider three different types of communications systems: vehicular ad hoc networks, maritime ad hoc networks, and underwater acoustic networks to deal with the developing requirements of their applications by ensuring safe and stable communications; and intend to overcome the existing issues in each of them. Both vehicular and maritime ad hoc networks use electromagnetic radio waves as a medium of communications, whereas underwater acoustic networks use acoustic waves.

Ubiquitous wireless communications is an essential goal for numerous applications ranging from traffic safety to entertainment-related information for various users either on the land, the sea surface or in the ocean. The dedicated licensed spectrum for each of these communications systems has been found insufficient to fulfill the increasing needs of vehicular, maritime, and underwater applications. To alleviate the spectrum scarcity in these networks, cognitive technology is a viable solution as it can utilize spectrum in

an environment-friendly manner (i.e., avoiding harmful interference with licensed users). To this end, stable links are essential for communications with different users in order to meet the growing demands of vehicular, maritime, and underwater applications. A link is formed only when two communicating nodes have consensus about a common idle channel. Therefore, novel cognitive routing protocols are required for each of these networks to ensure cooperation among the respective users; thereby retaining stable links for vehicular, maritime, and underwater communications.

Various routing techniques have been proposed for vehicular, maritime, and underwater networks, but the number of routing protocols that consider cognitive capability with a routing technique is very limited for vehicular networks. Nevertheless, safe and stable communications issues for cognitive vehicular networks are still under investigation in order to reach a robust and distinguished solution. Similarly, for maritime and underwater networks, combining cognitive principles with routing schemes have not yet been considered. Therefore, in this thesis, we first propose cognitive routing protocols that ensure stable routes between sources and destinations in order to overcome the problems of spectrum scarcity and high latency in vehicular, maritime, and underwater networks, respectively. Our goal is to maintain network stability by considering spectrum sensing and routing simultaneously for vehicular, maritime, and underwater communications. We prove better network performance in each of these cognitive routing protocols in terms of end-to-end delay, delivery ratio, and routing overhead. From these results, we observe that the performance of these networks can be further improved by considering a logically centralized controller that has a global view of the network states and is responsible for selecting the stable paths. This is only possible with the physical separation of network control plane and the forwarding plane.

Therefore, we then apply a new concept of software-defined networking (SDN)

in these cognitive vehicular, maritime, and underwater networks to further overcome the shortcomings with the existing architectures in these domains. We find that the SDN-based cognitive routing protocols for each of these vehicular, maritime, and underwater networks improve network performance in comparison with non-SDN-based cognitive routing protocols. All nodes in non-SDN based networks perform all functions (routing, forwarding, and network management) individually resulting in an inefficient utilization of resources, high latency, and large amounts of overhead. Due to SDN approach, these nodes do not further need to configure individually. Any change in the network can be now done centrally by the logically centralized controller. We further comprehend from these results that the improvement is only for networks with specific applications. In order to support multiple applications simultaneously under the same infrastructure and enable users to satisfy each application service with improved network flexibility, we finally introduce two integrated architectures. The first one supports different vehicular applications with the integration of software-defined networking, network function virtualization, and fog computing. However, the second one is an integrated coastal city that instate cognitive vehicular-to-ship communications in hybrid environments. Consequently, we end up this thesis opening a new door for routing in integrated cognitive vehicular and maritime networks in order to run multiple applications simultaneously under the same infrastructure.

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Nomenclature

Notation Description

CR	Cognitive Radio
PU	Primary User
VANET	Vehicular Ad Hoc Network
V2V	Vehicle-to-Vehicle
V2I	Vehicle-to-Infrastructure
RSU	RoadSide Unit
SANET	Ship Ad Hoc Network
S2S	Ship-to-Ship
CA	Cognitive Acoustic
UAN	Underwater Acoustic Network
OSAR	OFDM-based Spectrum-Aware Routing
SDN	Software-Defined Networking
CR-SDVN	Cognitive Radio Software-Defined Vehicular Network
MC	Main Controller
LC	Local Controller
CR-SDMN	Cognitive Radio Software-Defined Maritime Network
ASV	Autonomous Surface Vehicle
CA-SDUN	Cognitive Acoustic Software-Defined Underwater Network
AUV	Autonomous Underwater Vehicle
FC	Fog Computing
NFV	Network Function Virtualization
V2S	Vehicle-to-Ship

Chapter 1

Introduction

1.1 Motivation

Safe and stable wireless communications with ubiquitous networking is an essential goal for numerous vehicular, maritime, and underwater applications. The vehicular ad hoc network is an advancing technology that allows vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications in order to facilitate various applications ranging from road safety to entertainment-related information for passengers [1]. Similarly, maritime communications play an essential role in providing variety of services to users aboard. These services include ship navigation, ship traffic management, location, and all other entertainment-related information for passengers aboard [2]. In the same way, underwater acoustic communications systems have been attracting significant interest in the last decade in order to deal with various applications for scenarios ranging from the depths of the ocean to the surface of the ocean. These applications include underwater resource exploration, environmental monitoring, target tracking, oceanography data collection, and marine animal study [3–5]. Due to the increasing demand for road safety, the increase in number of marine users, and emerging demands of underwater applications; establishing stable routes with an efficient routing

scheme are a key challenge for each of these communication systems. Also, communication between two nodes is only possible if both have consensus about free spectrum. The dedicated short range communications (DSRC) spectrum, an amendment to IEEE 802.11 (also known as WAVE 802.11p) for automobile communications only [6], high frequency (HF), very high frequency (VHF), and ultrahigh frequency (UHF) radios for maritime communication systems [7], and acoustic spectrum band from 1 to 40 kHz [8] have been found insufficient for growing vehicular, maritime, and underwater requirements, respectively. Therefore, to support the above-mentioned applications for each system, spectrum availability is one of the major concerns.

To fulfill the increasing needs of these communication systems, licensed spectrum can be utilized in an environment-friendly manner by unlicensed users while keeping the licensed users safe. For that reason, cognitive radio was announced as an enabling technology to resolve the spectrum scarcity issues in vehicular and maritime ad hoc networks [9], whereas cognitive acoustic is a viable solution for underwater acoustic networks [10]. We mention here that both vehicular and maritime ad hoc networks use electromagnetic radio waves as a communication medium, whereas underwater acoustic networks use acoustic waves for communication. Therefore, the performance of vehicular and maritime networks can be improved by leasing additional spectrum outside the licensed band (e.g., TV bands and WS (white space), respectively) [11, 12]. Whereas, the spectrum scarcity in underwater networks can be alleviated by utilizing acoustic spectrum in an environmental-friendly manner (i.e. avoiding harmful interference with natural acoustic systems) and in an efficient manner (i.e. high spectrum utilization) [10] as the underwater communication systems include both natural acoustic systems (e.g. marine mammals) and artificial acoustic systems (e.g. sonar systems). Thus, in order to meet the growing demands of vehicular, maritime, and underwater applications, a stable cognitive link is essential for communications be-

tween different users. A link is formed only when two communicating nodes have consensus about a common idle channel. Consequently, new cognitive routing protocols are required to provide stable links for vehicular, maritime, and underwater communications by ensuring cooperation among vehicles, ships, and acoustic users, respectively.

Routing is a process that helps nodes (vehicles, ships, and acoustic users) to establish a stable link to forward a message to its destination. It is a challenging task to implement routing protocols for cognitive-based vehicular ad hoc networks, maritime ad hoc networks, and underwater acoustic networks that consider spectrum scarcity and sparse network issues together. Therefore, research in this venue is in its infancy. Moreover, selection of relay nodes is a key design factor in cognitive-based vehicular ad hoc networks, maritime ad hoc networks, and underwater acoustic networks in order to maintain stable links to reach destinations, and to cope with three things: (i) the shortcomings of various signal obstacles in different scenarios (city, highway, sea environment, and underwater environment), (ii) the network conditions in these scenarios, and (iii) spectrum availability. For that reason, there is a need to propose a routing protocol for each of these networks in order to improve the overall network performance by electing a relay node that incurs the minimum delay when sending a packet to its destination. Hence, in this thesis, we propose novel routing protocols for cognitive-based vehicular ad hoc networks, maritime ad hoc networks, and underwater acoustic networks, respectively that ensure stable links between source and destination. These proposed cognitive routing protocols are applicable to different respective scenarios (e.g., highway, city, calm, moderate and high sea conditions). Subsequently, forming a cognitive radio vehicular ad hoc network, a cognitive maritime network, and a underwater cognitive acoustic network that guarantee stability and sustainability for different scenarios are the primary aims of this study.

1.2 Objective

The main objective of this thesis is to combine cognitive capability with routing techniques in order to overcome the problems of spectrum scarcity, intermittently connected networks, high latency, and large overhead in vehicular, maritime, and underwater networks. The thesis proposes cognitive routing protocols for each of these vehicular, maritime, and underwater networks with and without using SDN technology. These novel cognitive routing protocols improve spectrum opportunities and network stability for different users communicating with each other on land, the sea surface, and in the ocean. The goal is to select the best routes between sources and destinations for each of these networks that incurs the minimum delay to reach destinations. In a nutshell, each querying node in all these schemes selects the next-hop node that meets two conditions: (i) Both nodes have consensus about a common idle channel. (ii) The selected next-hop node has the minimum delivery time to the destination from among all its neighbors.

1.3 Contribution and thesis outline

This dissertation simultaneously considers spectrum sensing and routing for different scenarios on land, the sea surface, and in the ocean. The thesis first proposes non-SDN-based cognitive routing protocols for vehicular maritime and underwater networks to improve spectrum opportunities and network stability. Later, by considering SDN technology in each of these cognitive routing protocols for vehicular, maritime, and underwater networks, the thesis further improves network performance due to logically centralized controller which separates network control layer from data layer. The rest of the thesis is organized into eight chapters as follows:

- **Chapter 2:** presents a novel hybrid technique for cognitive radio vehicular ad hoc networks that continuously switches between V2V and V2I communications. Both highway and city scenarios are considered in this scheme. Each scenario considers both dense and sparse network conditions. The objective is to minimize message delivery time in order to improve network performance by simultaneously considering spectrum scarcity and network connectivity issues for both city and highway scenarios, the selection between two scenarios differs in each case due to different road trajectories.

- **Chapter 3:** proposes a novel scheme for cognitive maritime ad hoc network to find a stable path between source and destination based on belief propagation algorithm. This algorithm allows each ship to send the local sensing results obtained from energy detection scheme to all the neighbors in its communication range. Then, each ship combines its belief with the beliefs of all its neighbors to make a final belief about the existence of primary user. Finally, the best stable path is selected using two well-known routing protocols by finding minimum link duration between source and destination with their beliefs.

- **Chapter 4:** combines cognitive capability with a routing technique in order to overcome the problems of spectrum scarcity and high latency in underwater cognitive networks. OFDM-based spectrum-aware routing performs spectrum sensing to evaluate the surrounding environment, and then finds the best relay node to deliver packets to the destination. The querying node first finds a common idle channel by comparing its local sensing results with all the neighbors within the transmission range, and then selects a relay node for the next hop that has the minimum transmission delay. Two sensor nodes can only communicate while protecting the activity of both natural acoustic users and artificial acoustic users if they find a common free channel.

- **Chapter 5:** proposes a novel cognitive routing protocol for software-defined vehicular networks is proposed to find a stable route between source and destination. The technique simultaneously considers spectrum sensing and routing based on SDN. Local controllers are selected to serve as a gateway between vehicles and the main controller. In this manner, the technique continuously switches between V2V and V2I communications in order to overcome spectrum scarcity and network connectivity issues.

- **Chapter 6:** presents the cognitive radio software-defined maritime network, which ensures cognitive routing in marine networks based on a new approach of SDN, in order to find a stable route between source and destination. Ships moving for a planned mission are considered as clusters where cluster heads perform the role of local controllers. The technique considers autonomous surface vehicles to relay data between marine users close to the seashore and at deep sea. The SDN is applied for the first time using a combination of a cognitive capability and a routing technique in maritime networks in order to overcome the problems of limited services altogether due to the high cost of satellite links, spectrum scarcity, and high latency.

- **Chapter 7:** proposes the cognitive acoustic software-defined underwater network, which ensures cognitive routing in underwater sensor networks based on SDN, in order to find a stable route between source and destination. Autonomous underwater vehicles moving in fixed trajectories serve as local controllers. In this manner, the technique improves the spectrum opportunities and network stability for different users communicating with each other in the ocean.The SDN is also applied for the first time using a combination of a cognitive capability and a routing technique for underwater cognitive acoustic networks, in order to overcome the problems of limited services altogether due to application constraints, spectrum scarcity, and high latency.

- **Chapter 8:** opens a new door for routing in cognitive networks by integrating software-defined networking, network function virtualization and fog computing. Two types of integrated networks are proposed in this chapter in order to fulfill the demands of different users for different applications. These novel routing schemes select paths from sources to destinations in order to run multiple applications simultaneously under the same infrastructure. This means that this integration can divide the tasks into smaller ones by performing them at the local server instead of central server to preserve latency.

- **Chapter 9:** summarizes the thesis with some future research directions that need to be explored further.

Chapter 2

Cognitive Radio Vehicular Ad Hoc Networks

2.1 Introduction

The vehicular ad hoc network (VANET) is an up-and-coming technology that allows vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications in order to facilitate novel, inspiring services and safe driving experiences for passengers. It is a distributed networking technique in which vehicles can join and depart from the network in a dynamic manner, thereby forming an ad hoc network by deploying wireless technology. It is indubitable that the VANET is a special class of mobile ad hoc network (MANET); nevertheless, the extremely mobile nature and perpetually changing topology of vehicles makes VANETs relatively different from MANETs. Vehicular communications plays an important role in dealing with various vehicular applications ranging from road safety to entertainment-related information for passengers [1]. With the increasing demand for road safety, there is a need to design a novel protocol that ensures stability by considering both

V2V and V2I communications. However, existing work on VANETs [13, 14] has provided several reputable solutions for safe and stable communications among vehicles, but some communications issues are still under investigation to reach a robust and distinguished solution in this research venue [15].

Ubiquitous vehicular communications is an essential goal for numerous intelligent transportation system (ITS) applications. The dedicated short range communications (DSRC) spectrum, an amendment to IEEE 802.11 (also known as WAVE 802.11p) has been found insufficient to fulfill the increasing needs of vehicular communications systems [6]. Therefore, to support the above-mentioned vehicular applications, spectrum availability is one of the major concerns. Keeping in mind that DSRC channels are reserved for automobile communications only, their inadequacy may degrade the performance of vehicular networks. For that reason, cognitive radio (CR) was announced as an enabling technology to resolve the spectrum scarcity issue in VANETs [9]. The performance of vehicular networks can be improved by leasing additional spectrum outside the DSRC band (e.g., TV bands) [11]. Therefore, an algorithm is required to detect the presence/absence of the primary user (PU), thereby ensuring PU activity safety. Another major concern in CR-VANETs is the accuracy of hypotheses about spectrum availability, because individual sensing results do not assure a high probability for spectrum availability. This issue can be resolved by cooperation among users in order to increase transmission opportunities for different CR users, but cooperation for different network architectures poses different challenges [16]. For instance, to improve the detection performance, cooperative spectrum sensing has been shown to be an effective method in CR networks [17], but cooperative sensing schemes among vehicles incur high overhead. Therefore, a distributed fixed infrastructure, or the roadside unit (RSU), appears to be a righteous solution for this issue.

An RSU is a computing device (sensors and micro-controllers) located on the road-

side that provides connectivity and decision support to passing vehicles [18]. RSUs can be used as a storage device by collecting updated information (channel state and network state) from cars passing within transmission range. And it can act as a relay node to pass aggregated information to the next-hop vehicle/RSU, thereby improving network connectivity. Not surprisingly, each scenario (city or highway) in VANETs faces both dense and sparse network conditions. In view of that, RSUs can be used to improve network performance by keeping updated information to support passing vehicles and by relaying packets to enable successful delivery. Therefore, in order to meet the growing demands of vehicular applications, a stable cognitive link is essential for communications with different vehicles and RSUs. A link is formed only when two communicating nodes (either V2V or V2I) have consensus about a common idle channel. Consequently, a new cognitive routing protocol is required to provide stable links for vehicular communications by ensuring cooperation among vehicles and RSUs.

Routing is a process that helps vehicles to establish a stable link to forward a message to its destination. Several routing protocols have been proposed for VANETs in city or highway (or both) scenarios to support various vehicular applications, such as Greedy Perimeter Stateless Routing (GPSR) [19], static-node assisted adaptive routing protocol in vehicular networks (SADV) [20] and geographic delay tolerant network routing with navigator prediction (GeoDTN + Nav) [21] to list a few. However, it can be clearly observed from the literature [13, 22] that these protocols incur high overhead and have path stability issues due to disjointed network conditions. Therefore, research in VANETs has recently taken a new direction by implementing routing protocols with the aid of RSUs. Roadside units as message routers (ROAMER) [23] is the first protocol in VANETs proposed for city scenarios that exploits the RSU backbone to efficiently route packets to distant locations by using geographic forwarding. Likewise, roadside unit based hybrid routing protocol (RSU-

HRP) [24] and Hybrid Road-Aware Routing (HRAR) [25] are other protocols that consider RSUs at junctions.

None of these existing routing protocols for VANETs consider spectrum scarcity issues caused by the inadequacy of DSRC channels. Recent studies have developed very few schemes in this direction to overcome scarcity issues for VANETs. Huang *et al.* [18], Abbassi *et al.* [26], and Baraka *et al.* [27] proposed novel algorithms by considering spectrum sensing measurements to access the channel state on different road segments. All these studies developed schemes to overcome only the spectrum scarcity problem in CR-VANETs. A routing scheme considering both spectrum and routing issues together was proposed by Kim *et al.* [28]. *CoRoute* is one of the routing protocols in the area of CR-VANETs for city scenarios that makes the best use of available Wi-Fi bandwidth by causing fewer disruptions to residential users. Similarly, [29] and Spectrum-Aware Beaconless (SABE) geographic routing [30] were also proposed for CR-VANETs.

All of these routing protocols in CR-VANETs have some restrictions on the selection of both channel and relay node. These protocols make several assumptions to improve the success rate. Therefore, several issues for routing in CR-VANETs (like path instability and high latency due to selection of both channel and relay) are still unresolved. As a consequence, combining cognitive principles with routing schemes to design an algorithm by taking into consideration V2V and V2I communications together has not yet been considered. Thus, research in this venue is in its infancy. Moreover, selection of relay nodes is a key design factor in CR-VANETs in order to maintain stable links to reach destinations, and to cope with three things: 1) the shortcomings of various signal obstacles in city and highway scenarios, 2) the network conditions in these scenarios, and 3) spectrum availability. For that reason, there is a need to propose a routing protocol in order to improve the overall network performance by electing a relay node that incurs the minimum delay when sending

a packet to its destination. Hence, in this chapter, we propose a novel routing protocol for CR-VANETs that ensures a stable link between source and destination by considering both V2V and V2I communications. This proposed cognitive routing protocol is applicable to both highway and city scenarios. Subsequently, forming a CR-VANET that guarantees stability and sustainability for different scenarios is a primary aim of this study.

A novel technique that provides simultaneous spectrum sensing and routing is proposed in this chapter. It is a hybrid technique that continuously switches between V2V and V2I communications in order to overcome spectrum scarcity and network connectivity issues. Spectrum sensing is done by a belief propagation (BP) [31] algorithm that iteratively combines the beliefs of all neighboring vehicles to determine a final belief. Based on this final belief, each node determines the availability of a channel, which helps in selecting a relay node. Because two nodes can only communicate if they both have consensus about a common idle channel, channel selection is a fundamental step for relay node selection. Both highway and city scenarios are considered. Each scenario considers both dense and sparse network conditions. As our objective is to minimize message delivery time in order to improve network performance by simultaneously considering spectrum scarcity and network connectivity issues for both city and highway scenarios, the selection between two scenarios differs in each case due to different road trajectories.

The remainder of this chapter is organized as follows. In Section 2.2, we propose the belief propagation–based infrastructure–aided hybrid cognitive routing algorithm. Section 2.3 discusses simulation performance results; and finally, Section 2.4 concludes the chapter.

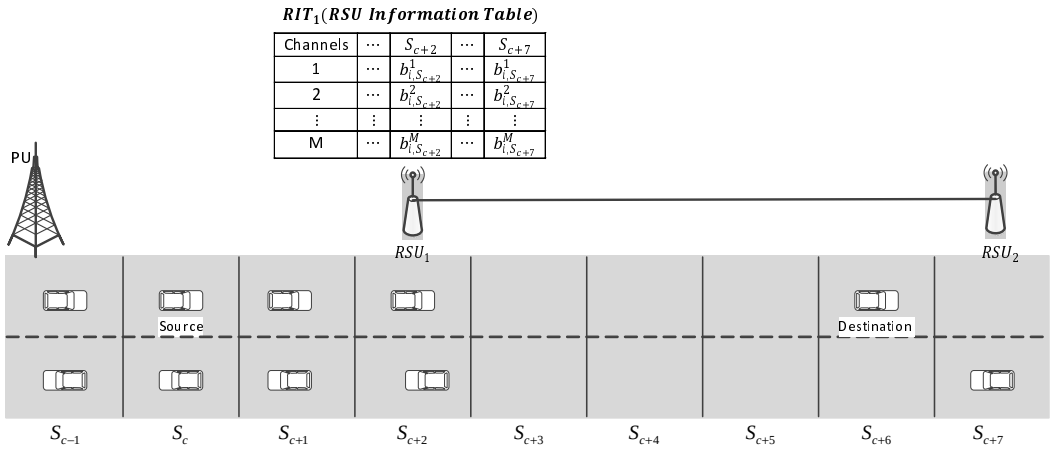


Figure 2.1: Highway model.

2.2 Proposed hybrid cognitive routing protocol

We propose a hybrid cognitive routing protocol for V2V and V2I communications in both highway and city scenarios. We use the term *hybrid* because the routing protocol switches between V2V and V2I communications. The purpose of this routing algorithm is to enable vehicles to efficiently overcome spectrum scarcity along with network connectivity issues.With the aid of RSUs within the considered network, the proposed algorithm aims to provide a stable link between communicating nodes, even under sparse network conditions. A stable link is maintained by jointly selecting the channel and relay node in an efficient and reliable manner. Cooperation among vehicles is the key factor for both selections to be done proficiently. Relay selection is dependent on channel selection in such a way that two nodes can only communicate if they both have consensus about a common idle channel. For that reason, the primary task of the proposed routing algorithm is to sense the spectrum with the aid of RSUs. To accomplish this task, we apply collaborative spectrum sensing using a BP algorithm to find a list of free channels for different road segments, and to then

$\boldsymbol{RIT_1(RSU\ Information\ Table)}$

Channels	Street A				Street B			
	$\cdots$	$S_{c-1,A}$	$S_{c+1,A}$	$\cdots$	$\cdots$	$S_{1,B}$	$S_{2,B}$	$\cdots$
1	$\cdots$	$b^1_{i,S_{c-1,A}}$	$b^1_{i,S_{c+1,A}}$	$\cdots$	$\cdots$	$b^1_{i,S_{1,B}}$	$b^1_{i,S_{2,B}}$	$\cdots$
$\vdots$	$\vdots$				$\vdots$			
M	$\cdots$	$b^M_{i,S_{c-1,A}}$	$b^M_{i,S_{c-1,A}}$	$\cdots$	$\cdots$	$b^M_{i,S_{1,B}}$	$b^M_{i,S_{2,B}}$	$\cdots$

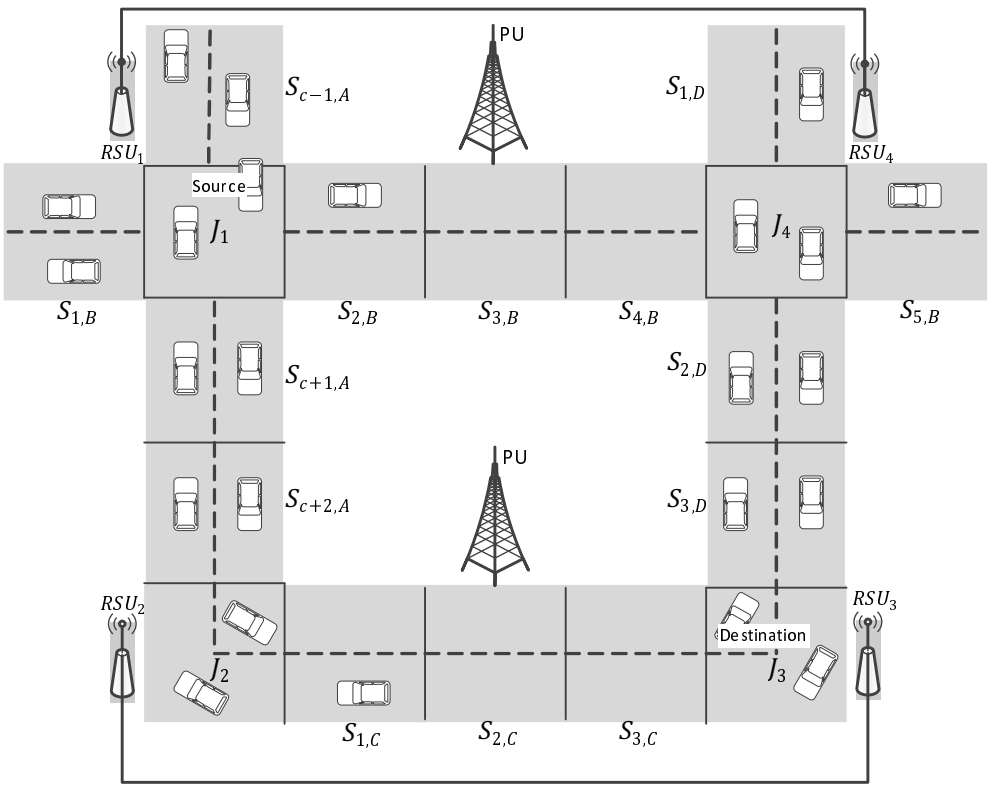


Figure 2.2: City model.

find the best relay node to deliver packets to the destination.

A cognitive vehicular network with V vehicles is shown in Figs. 2.1 and 2.2 for highway and city scenarios, respectively. To implement the BP algorithm for spectrum sensing in both highway and city scenarios, we consider the network model as a Bayesian graphical model, where each node represents a vehicle, and each edge is a communications link between two vehicles. All vehicles are assumed to be equipped with a GPS receiver

to get their current location. Vehicles periodically exchange locations and channel information with each other using common control channel, and update the nearby RSUs with gathered information. For reporting or beacon messages all vehicles are tuned to common control channel. RSUs are assumed to be installed along the roads at specific and adequate distances [26]. These RSUs are interconnected with each other via wired connections or through a high-bandwidth stable backbone connection, such that they can exchange their information tables in order to update vehicles about the future state of channels and relay nodes in the upcoming road segments with almost negligible delay [27,32]. Each RSU keeps a record of all vehicles in its coverage area. We designate an RSU information table as *RIT*, and for a vehicle, *VIT*. PUs are also assumed to be sited along the roadways at a fixed locations, as shown in Figs. 2.1 and 2.2. In a highway scenario, plenty of TV white space is available due to the lower population, whereas when considering a city scenario, the high population causes difficulty for cognitive vehicles trying to find idle spectrum [11]. Moreover, we divide each road into different segments of equal length, l, and we assume that digital maps are installed in each vehicle. Thereby, each vehicle is aware of information about the road segment and street, $S_{c,street}$, it is moving on. As Huang *et al.* did [18], to avoid complexity, we also assume that the channel state is the same within each road segment. The following subsection explains how vehicles perform spectrum sensing, and how RSUs maintain the information about channel state for each road segment in both highway and city scenarios.

2.2.1 Spectrum sensing in highway and city models

We perform spectrum sensing to detect the presence of the PU when vehicles are moving on roads. PUs are incumbent users that can be passengers in vehicles, or can be other users located in buildings, restaurants, etc., alongside the road utilizing other licensed bands,

such as TV bands (VHF and UHF), Wi-Fi, etc. [26,27,33]. We consider the cognitive radio spectrum as the TV spectrum in this work, and we divide the TV band into M channels. Spectrum sensing is done via energy detector scheme, in which each vehicle senses the spectrum individually and makes the local decision by following a binary hypothesis model:

$$x_{i,S_{c,street}}(t) = \begin{cases} n_{i,S_{c,street}}(t), \quad H_0 \\ \\ s_{i,S_{c,street}}(t) + n_{i,S_{c,street}}(t), \; H_1 \end{cases} \tag{2.1}$$

where $i = 1, ..., V$, $S_{c,street}$ represents the current segment and the name of the street on which vehicle i is moving (the index *street* is utilized for the city scenario only, because there are different streets; for a highway scenario, it is a straight road, as shown in Fig. 2.1); $s_{i,S_{c,street}}(t)$ is the PU signal received by vehicle i in the current segment and street, and $n_{i,S_{c,street}}(t)$ is additive white Gaussian noise (AWGN). The energy-based test statistic is given as follows:

$$x_{E_i} = \sum_{g=1}^{N} |x_i(g)|^2 \tag{2.2}$$

where N is the time–bandwidth product, and $x_i(g)$ is the gth sample of the received PU signal at vehicle i.

Each vehicle senses the spectrum for every segment it is moving on, and keeps a record of the information in its *VIT*. When a vehicle comes into the coverage area of an RSU, it exchanges its sensing information with the RSU, and both update their tables accordingly. As a result, each RSU updates vehicles about upcoming segments in advance. Vehicles perform collaborative spectrum sensing by using the BP algorithm. BP is an iterative algorithm in which vehicles exchange their local decisions to approximate marginal probabilities (i.e., beliefs about segments). Each vehicle calculates its local sensing result as an a posteriori probability. For calculation of local sensing results, we use the energy

detection scheme shown in (2.1) and (2.2). For each vehicle, the a posteriori probability for $S_{c,street}$ is calculated as:

$$\varphi^{f}_{i,S_{c,street}}(H_h) = P(H_h|x_{i,S_{c,street}}) = \frac{P(x_{i,S_{c,street}}|H_h)P(H_h)}{P(x_{i,S_{c,street}})} \tag{2.3}$$

where $f \in M$, $P(x_{i,S_{c,street}} \mid H_h)$ is the probability density function of normally distributed random variable $x_{i,S_{c,street}}$ conditioned on $H_h, (h = 0, 1)$, $P(x_{i,S_{c,street}})$ is the normalizing constant, and $P(H_h)$ is the prior probability, which is assumed to be constant for all vehicles. To calculate a belief about the state of vehicle j in segment $S_{c+1,street}$ estimated by vehicle i in segment $S_{c,street}$, vehicles i and j within transmission range of each other exchange their messages as:

$$\begin{aligned}\mu^{f}_{(i,S_{c,street})(j,S_{c+1,street})}(H_{j,S_{c+1,street}}) = w \sum_{H_{i,S_{c,street}}} \psi^{f}_{(i,S_{c,street})(j,S_{c+1,street})}(H_{i,S_{c,street}}, \\ H_{j,S_{c+1,street}})\varphi^{f}_{i,S_{c,street}}(H_{i,S_{c,street}}) \prod_{k\in(N_i-\{j\})} \mu^{f}_{(k,S_{c-1,street})(i,S_{c,street})}(H_{i,S_{c,street}})\end{aligned} \tag{2.4}$$

$\mu^{f}_{(i,S_{c,street})(j,S_{c+1,street})}(H_{j,S_{c+1,street}})$ describes a belief about the state of vehicle j in segment $S_{c+1,street}$ estimated by vehicle i in segment $S_{c,street}$, w is the weighting factor, the term $k \in (N_i - \{j\})$ denotes that k only belongs to the neighbors of i and not the neighbors of j, and $S_{c-1,street}$ represents the vehicles in all the previous segments that are connected to vehicles in $S_{c,street}$. For example, see Fig. 2.2, the city scenario, where the current segment is J_1, vehicles in $S_{c-1,street}$ are vehicles in $S_{c-1,A}$, $S_{1,B}$, and $S_{2,B}$ when j is in $S_{c+1,A}$, and they are vehicles in $S_{c+1,A}$, $S_{c-1,A}$, and $S_{1,B}$, when j is in $S_{2,B}$. On the other hand, for a highway scenario, it is just the previous segment, S_{c-1} (as shown in Fig. 2.1), and $\psi^{f}_{(i,S_{c,street})(j,S_{c+1,street})}(H_{i,S_{c,street}}, H_{j,S_{c+1,street}})$ is a compatibility function, which is defined

as:

$$\psi^{f}_{(i,S_{c,street})(j,S_{c+1,street})}(H_{i,S_{c,street}}, H_{j,S_{c+1,street}}) = \begin{cases} \eta & if\ H_{i,S_{c,street}} = H_{j,S_{c+1,street}} \\ 1-\eta & if\ H_{i,S_{c,street}} \neq H_{j,S_{c+1,street}} \end{cases} \tag{2.5}$$

The correlation among sensing data from different vehicles can be used to enhance the accuracy of hypotheses concerning spectrum availability [27, 34]. The compatibility function depends on the correlation between states $H_{i,S_{c,street}}$ and $H_{j,S_{c+1,street}}$. By changing the value of η, we control the correlation among vehicles in the two scenarios. The larger the value of η, the more the correlation between neighboring vehicles, and hence, the higher the detection accuracy.

Finally, the belief of each vehicle moving in its current segment and street is calculated as:

$$b^{f}_{i,S_{c,street}}(H_{i,S_{c,street}}) = w\ \varphi^{f}_{i,S_{c,street}}(H_{i,S_{c,street}}) \prod_{k\in(N_i)} \mu^{f}_{(k,S_{c-1,street})(i,S_{c,street})}(H_{i,S_{c,street}}) \tag{2.6}$$

On the basis of these beliefs, each vehicle and RSU makes a final decision about each segment, street, and channel as follows:

$$D^{f}_{i,S_{c,street}} = \begin{cases} H_0 & if\ b^{f}_{i,S_{c,street}}(H_0) > b^{f}_{i,S_{c,street}}(H_1) \\ H_1 & if\ b^{f}_{i,S_{c,street}}(H_0) < b^{f}_{i,S_{c,street}}(H_1) \end{cases} \tag{2.7}$$

2.2.2 Relay selection in highway model

To select the best relay node in order to make a stable route between source and destination, we propose a hybrid routing scheme by using sensing results obtained in the previous subsection. We exploit RSUs in this hybrid routing scheme as storage devices to assist vehicles in determining the future state of road segments, and as relay nodes for relaying packets in sparse network conditions. In a highway scenario, vehicles are assumed to be moving on a straight road in two-way directions. Also, we assume two separate lanes for vehicles moving in opposite directions (west-east and east-west) as shown in Fig. 2.1. Our objective is to minimize the message delivery time to the destination; therefore, our protocol selects a relay node that has the minimum delivery time from among all the nodes within transmission range of the querying node.

To initiate routing, each node first broadcasts a beacon message to all its neighboring nodes. We assume that vehicles periodically update each other with their current status by sending beacon messages, and we also assume that the source node knows the current position of the destination by using a reactive location service algorithm [35]. Each node updates its *VIT* by receiving beacon messages from neighboring nodes. A *VIT* for the highway scenario is shown in Table 2.1. The beacon message includes the following entities: vehicle's ID, position, velocity, time, and belief.

In the following expression:

$$\langle i, (x, y), v_i, t, b^{f^*}_{i,S_{c,street}}(H_0)\rangle \tag{2.8}$$

$f^* = (1, ..., M)$ is a set of idle channels estimated by vehicle i in segment $S_{c,street}$. The source node then calculates the message delivery time, MDT_{ij}, between itself and each

Table 2.1: Vehicular Information Table for highway.

VIT	***Previous segment***	***Current segment***	***Next segment***
IDs	j	i	k
position	(x_j, y_j)	(x_i, y_i)	(x_k, y_k)
velocity	v_j	v_i	v_k
time	t_j	t_i	t_k
belief	$b^1_{j,S_{c-1}}$, -, $b^3_{j,S_{c-1}}$, $b^4_{j,S_{c-1}}$, -	b^1_{i,S_c}, b^2_{i,S_c}, -, -, b^5_{i,S_c}	$b^1_{k,S_{c+1}}$, $b^2_{k,S_{c+1}}$, -, $b^4_{k,S_{c+1}}$, -

Table 2.2: Vehicular Information Table for anchor node.

Administrator VIT	***Anchor Point***	***Street A***	***Street B***
IDs	i	j	k
position	(x_i, y_i)	(x_j, y_j)	(x_k, y_k)
velocity	v_i	v_j	v_k
time	t_i	t_j	t_k
belief	-,$b^2_{i,S_{c,J_1}}$,-,-,$b^5_{i,S_{c,J_1}}$,	$b^1_{j,S_{c+1,A}}$, -, -,-, -,	$b^1_{k,S_{2,B}}$, -, -,-, $b^5_{k,S_{2,B}}$
degree of sparsity	$-$	$\delta_{S_{c+1,A}}$	$\delta_{S_{2,B}}$

relay node within its transmission range as follows:

$$MDT_{ij} = \frac{R \pm d_{ij}}{\sqrt{(v_i \cos\theta_i - v_j \cos\theta_j)^2 + (v_i \sin\theta_i - v_j \sin\theta_j)^2}} \times min(Ch^1, Ch^2, ..., Ch^M) \tag{2.9}$$

$min(Ch^1, ..., Ch^M)$ represents the channel that has the highest belief among all the beliefs for a set of idle channels $f^* = (1, ..., M)$, whereas each common channel Ch^{f^*} between vehicle i and vehicle j is calculated as $Ch^{f^*} = 1 - min\left(b^{f^*}_{i,S_{c,street}}(H_0), b^{f^*}_{j,S_{c+r,street}}(H_0)\right)$.

R is the transmission range of vehicles, d_{ij} is the distance, and θ_i is the angle with respect to the destination (i.e., $tan^{-1}\frac{y_D-y_i}{x_D-x_i}$). The numerator $R \pm d_{ij}$ helps finding the node that is farthest from the querying node, the angle finds the one that must be moving towards destination, and v describes how quickly a node will leave the transmission range of querying node. r is a range size that can be any of the next segments within transmission range of vehicle i in segment $S_{c,street}$, which will be described in the following subsection in detail. We consider two cases for each highway and city scenario: when the network is connected, and when the network is sparse. In the following, we will jointly discuss both cases for the highway scenario.

2.2.2.1 Message delivery time under sparse and connected network conditions for a highway scenario

When each segment on a highway has at least one moving vehicle, we consider the network fully connected. This is the case when RSUs collect information from nearby passing vehicles, update the *RIT*, and keep the record to facilitate vehicles in any disconnected segment in future. Usually, the vehicles on highways have very sporadic links, such that they are fewer in number on most portions of the roads, and are high in number on other portions, as shown in Fig. 2.1. Depending on network conditions, highway vehicles serve as information consumers and information providers, whereas RSUs in both scenarios occasionally function as a future predictor and sometimes act as a relay node. We define each role in the following ways.

- **Information consumer**. A vehicle within transmission range of an RSU acts as an information consumer when it receives an *RIT* and updates its *VIT* about the channel state in future segments.

- **Information provider.** At the same time, vehicles serve as information providers when

RSUs collect sensing information from nearby passing vehicles and keep a record of the segments in their RIT up to range size r. Range size r is the number of road segments within the coverage area of one RSU. Vehicles periodically update their VIT with each other in order to avoid stale information, and they provide this information to a nearby RSU while moving. In this way, each vehicle can find the list of free channels for future segments up to r in advance.

- **Future predictor and relay node.** Accordingly, an RSU functions as a future predictor when it shares the RIT with moving vehicles, and it acts as a relay node when a vehicle fails to find any other vehicle within its transmission range to deliver a packet to the next relay node/destination.

In the following, we explain in detail how a source node selects the best relay node by discussing the dual role of cars and RSUs using our example highway scenario.

i. Cars acting as information consumers, and the RSU as a future predictor: Let us assume some vehicles are moving on a highway, as shown in Fig. 2.1. The vehicles are moving in both clockwise and counterclockwise directions. The source vehicle in segment S_c receives an RIT and updates its VIT accordingly to get channel information about future segments. To deliver its message to a destination in segment S_{c+6}, it sends a beacon message to all the neighbors within transmission range and, from the *responses* it gets, calculates MDT using (2.9) for each neighbor node. Then, it selects the best relay node by using the equation as follows:

$$min(MDT_{iN_1}, MDT_{iN_2}, ..., MDT_{iN_N}) \tag{2.10}$$

where $N_1, N_2, ..., N_N$ are neighboring nodes within i's transmission range. This is V2I communications where RSUs just serve as a future predictor to provide the channel

state in upcoming segments. The RIT helps the vehicles to communicate with each other quickly as it provides a list of free channels in future segments. Therefore, it reduces the time needed for vehicles to make a decision about selecting the channel for communications. We will show this time reduction in our simulation results.

ii. Cars acting as information providers, and an RSU acting as a relay node: Fig. 2.1 shows both connected and sparse network conditions. When the packet reaches segment S_{c+2}, there is no vehicle to relay it to the destination. Here, the protocol again switches to V2I communications and sends the packet to its nearby RSU, where it quickly relays the packet to the destination. At this instant, three cases may occur for channel selection:

- If RSU_1 and the querying vehicle j are in the same segment (i.e., S_{c+2}), then vehicle j selects the channel that has a high probability of the idle state from among all the channels in its VIT for the current segment.
- If relay j and RSU_1 are in different segments, but they are within transmission range of each other, then the common communicating channel from the corresponding VIT and RIT having a high probability of an idle state is selected.
- The third is a rare case that may occur in any cognitive vehicular network scenario, when simultaneously selecting channel and relay node is a challenging task. We propose the following solution for this special case. When there is no RSU_1 within transmission range vehicle j applies a store-carry-and-forward approach. In this method, vehicle j holds the packet until it reaches the coverage area of RSU_1 or any other vehicle in order to relay the packet. And when there is no free channel between the RSU and the vehicle, the vehicle again applies the store-carry-and-forward approach until it enters a segment having a common idle

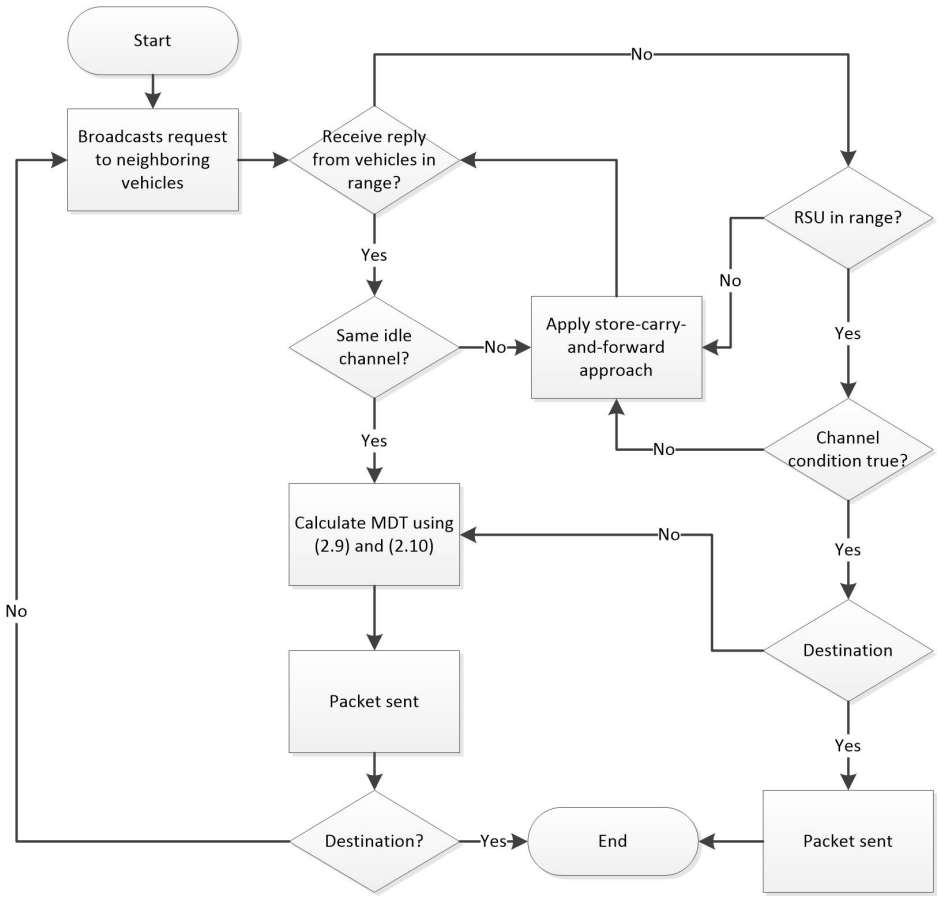


Figure 2.3: Flowchart representing the proposed scheme for the highway scenario.

channel with an RSU within transmission range. A delay may occur with this approach, but that is more acceptable than dropping the packet.

RSU_1 transfers the packet to RSU_2 via wired connection. When RSU_2 functions as a relay node, it uses (2.9) to locate the destination; it repeats the above procedure to deliver the packet to the destination if the destination is not within transmission range. Hence, this hybrid protocol reduces the MDT in either case (when communications is V2V or when it is V2I) for both dense and sparse network conditions. The flow chart for relay and channel selection for the highway scenario is shown in Fig. 2.3.

2.2.3 Relay selection in city model

In this subsection, we consider cognitive hybrid communications in the city scenario to establish a stable route between source and destination. The city scenario as shown in Fig. 2.2 is a combination of different straight roads that are connected with each other by junctions in different directions. The junctions are the key points, called anchors, that serve as the network brain where decisions are taken. These anchors are responsible for improving the overall network performance by making the right decision, especially in city scenarios, for CR-VANETs. Anchors update neighboring nodes and RSUs about the network condition on each street they are connected to. Like the highway model, the primary task of vehicles in an urban scenario is to perform spectrum sensing and update each other with the channel state. RSUs can be cameras in traffic lights and road signs; therefore, they are deployed only at the anchors.

For the urban scenario, communication among vehicles occurs in two modes: anchor mode and normal mode. Vehicles are in normal mode until or unless they are not at an anchor. Any vehicle at an anchor performs the function of a network monitor that decides to which street a packet should be forwarded, and the vehicle responsible for relaying the packet follows that decision. In the urban scenario, vehicles are assumed to be moving in all four directions (west-east, east-west, north-south, and south-north). Our goal is to minimize the message delivery time to the destination; therefore, our protocol selects a vehicle or RSU as the next relay node (depending on the network condition) to deliver the packet in minimum time.

Routing in the urban scenario is done in the following manner. We consider the same assumptions made in the previous subsection for destination's location and exchange of beacon messages. In anchor mode, an anchor node updates its VIT with message responses

it receives from its neighboring nodes, and selects a relay node in the street that has the minimum MDT. There is a slight modification when calculating MDT in this case. It depends on degree of sparsity as described by (2.11). As a result, minimum degree of sparsity means the street that has high connectivity is selected by the anchor node. Each anchor node (before leaving the anchor point) shares updated information with the RSU in order to retain the information at other anchor points. Because RSUs are interconnected, any vehicle can obtain the RIT of a specific anchor from anywhere (although it must be within the RSU's transmission range) to keep itself and other neighboring vehicles updated in advance. The VIT of an anchor node is shown in Table 2.2, which includes an extra entity called the degree of sparsity, $\delta_i = 1 - (no.\ of\ vehicles/length\ of\ segment)$. Vehicles in normal mode are those moving on streets away from anchor points. It is the responsibility of only the anchor node to calculate the degree of sparsity. Once a decision about the street is taken by the anchor node, relaying the packet to the destination is the same as in our highway model. Each node updates its VIT by receiving beacon messages from neighboring nodes.

The calculation of MDT_{ij} for different modes is different. Nodes in normal mode that intend to calculate MDT_{ij} use (2.9), whereas for those in anchor mode, MDT is calculated as:

$$MDT_{ij} = \frac{R \pm d_{ij}}{\sqrt{(v_i \cos\theta_i - v_j \cos\theta_j)^2 + (v_i \sin\theta_i - v_j \sin\theta_j)^2}} \delta_{ij} \times min(Ch^1, Ch^2, ..., Ch^M) \tag{2.11}$$

For the city scenario, we also consider two cases: when the network is connected and when the network is sparse. In the following, we will jointly discuss both cases.

2.2.3.1 Message delivery time in sparse and connected network conditions for the city scenario

We intend to solve the problem of sparse network conditions in CR-VANETs for the urban scenario in this section. By taking advantage of anchor points, our protocol tries to avoid streets that have less connectivity. Like the highway scenario, vehicles can only communicate with each other if they have consensus about a common idle channel. Therefore, using beliefs from Section 2.2.1, vehicles and RSUs find a stable route to deliver the packet successfully to the destination with the minimum transmission time by performing a dual role in each case. For the urban scenario, vehicles serve as an administrator as well as a follower, whereas RSUs function in the same manner as they do in the highway scenario. Following are the definitions of these roles.

- **Administrator.** A car acts as an administrator when it is at the anchor point. The administrator updates its *VIT* from the messages it receives from its neighbors in response to a request message. Before leaving the anchor point, an administrator shares the updated *VIT* with the RSU.

- **Follower.** After an administrator selects the relay node, a car serves as a follower and executes the same procedure using (2.9) and (2.10) to select the next relay node, until it reaches another anchor point.

- **Future predictor.** An RSU functions as a future predictor when it provides information about future segments to moving vehicles. In the urban scenario, RSUs are installed only at the anchors. Hence, RSUs are updated by nearby passing vehicles (either an administrator or a follower within transmission range). In this way, the RSU keeps a record of the information on segments up to r.

- **Relay node.** However, an RSU acts as a relay node when an administrator fails to find any street with high connectivity within transmission range to relay the packet.

In the following section, we discuss routing in detail, while taking into account the dual role of cars and RSUs, by means of our example city scenario.

i. Cars acting as administrators and RSUs acting as future predictors: Fig. 2.2 shows the vehicles moving in the city scenario. The source vehicle in segment J_1, which is an administrator, sends a beacon message to all neighboring nodes using (2.8), with position of the destination as an add-on. Receiving each reply from neighboring nodes, the administrator calculates the degree of sparsity and the MDT using (2.11), and updates its VIT as shown in Table 2.2. Then, it selects the relay node that satisfies (2.10). In our example city scenario, the source is the administrator node that finds street A as a highly connected street, and relays the packet on that street. The RSU provides the channel information about future segments on demand when an administrator fails to receive any reply message from its neighbors, thereby enhancing network connectivity and route stability while serving as a future predictor.

ii. Cars acting as followers, and RSUs acting as relay nodes: The relay node selected by the administrator plays the role of follower, which further routes the packet by using (2.9) and (2.10). As shown in Fig. 2.2, when the querying vehicle reaches J_2, the administrator does not find a connected street; the only street (i.e., C) is sparse. The protocol now switches to V2I communications, where the RSU at J_2 acts as a relay node and quickly transfers the packet to the next RSU at J_3, which in turn, transfers it to the destination. One might ask why the administrator at J_1 did not consider RSU_1 as a relay node and quickly deliver the packet to the destination. Yes, it can deliver the message more quickly, but the basic purpose of the RSUs in this proposed

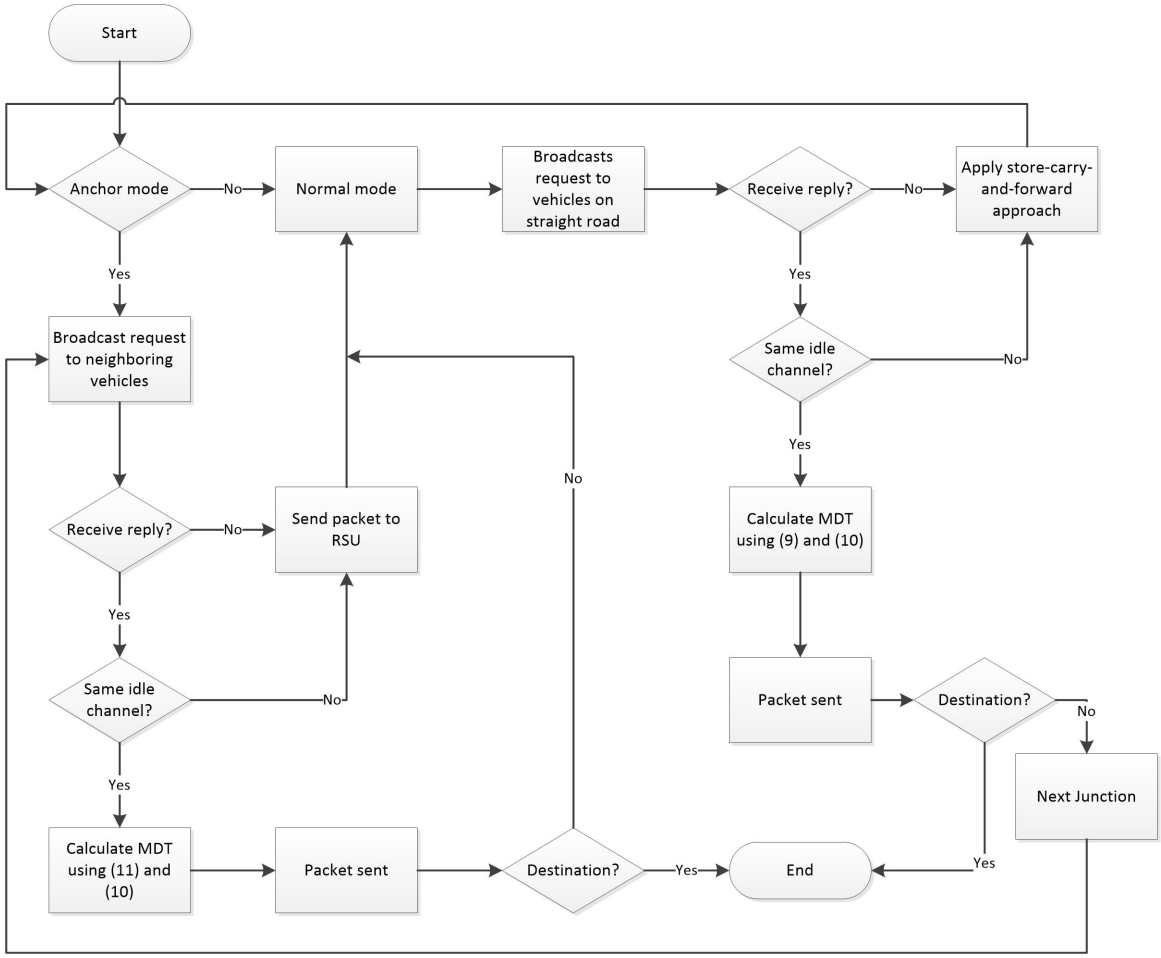


Figure 2.4: Flowchart representing the proposed scheme for the city scenario.

scheme is to keep a record of idle channels to deal with the spectrum scarcity issue. It only serves as a relay node when a querying node does not find any other option, as depicted by our example scenario in Fig. 2.2. This is because we do not want to burden the RSUs with more information, and we also do not help the network with a large number of RSUs, due to the cost issue. Our algorithm tries to find the fewest possibilities to make the communications V2I when selecting a relay node.

In our protocol, vehicles cooperate with each other to relay the packet. The

administrator plays a key role in the city scenario. It helps the network by predicting the future state for both spectrum availability and node density on the street. Fig. 2.4 shows a flow chart of the comprehensive algorithm for the city scenario by showing how the administrator/relay selects a highly connected street and the next-hop nodes in cooperation with free channels to reach the destination.

2.3 Simulation results and discussion

To the best of our knowledge, there is no publicly known simulator model for CR-VANETs in NS-2. Several models have been proposed in literature for CR networks, but they are not fulfilling all the requirements of cognitive radio sensor networks (CRSNs). Bukhari *et al.* [36] proposed a simulation model for CRSN that provides support for combined features of wireless sensor networks and CR based sensor networks. According to authors, this simulator model can be applied to any sort of wireless environment, but the accuracy of model in real world scenario and its implementation in CR-VANETs is not assured. Therefore, we evaluated the performance of this proposed scheme with NS-2. We divided the highway into 15 equal segments, each a 100 m length, l, and divided each straight road in the city scenario into eight equal segments with the same l as the highway scenario. The spectrum band was divided into $M = 5$, and each channel could be occupied by a licensed PU. The number of PUs in the highway scenario is three, and for the city scenario, five, each having a transmission range of 500 m. For the highway scenario, two RSUs were used, whereas four were used for the city scenario, each having a transmission range of 350 m. With the value $\eta = 0.9$, vehicles moved at various speeds (from 17 m/s to 30 m/s for the highway scenario, and from 6 m/s to 12 m/s for the city scenario). The number of relay nodes varied from 5 to 35, each having a transmission range of 250 m. The total number

of anchors, J, in the city scenario was four. Our simulation results are the average of more than 70 runs.

The radio channel for V2V and V2I communications is affected by both small-scale and large-scale fading in both city and highway scenarios. In general, there is no line of sight (LOS) path present between a primary transmitter and a secondary receiver. The receiver signal is the composite of various multipath components [37, 38]. Therefore, these faded signals may degrade the sensing performance. *Nakagami* distribution describes the statistical characteristics of both small-scale and large-scale fading [38, 39]. Because our proposed scheme is cognitive V2V and V2I communications, spectrum sensing is the first step to determining a free channel, and starts the communications process. Hence, in this chapter, we consider *Nakagami* distribution to model the fading of PU activity on the performance of the energy detector–based spectrum sensing scheme for both scenarios.

As argued in section 2.1, there is no publicly known cognitive routing algorithm for CR-VANETs that combines cognitive capability with a routing technique for both city and highway scenarios. Also, many existing implementation techniques are not reliable enough to compare a routing protocol for CR-VANETs in order to evaluate network performance. Therefore, we chose to compare our proposed scheme with the well-known routing protocol, Greedy Perimeter Stateless Routing (GPSR) [19]. It uses greedy forwarding to select the next hop in making links between the source and destination; however, our proposed scheme selects the next hop by making links based on the minimum delivery time between source and destination. Another reason for choosing GPSR is that both schemes broadcast beacon messages periodically to maintain up-to-date information in all neighboring nodes within transmission range of each other. Furthermore, in order to make GPSR a cognitive routing scheme, we simulated it in both city and highway scenarios in combination with the channel selection scheme proposed by Abbassi *et al.* [26] and refer to it as the reference scheme with

RSU. To evaluate the impact of utilizing RSUs in our proposed scheme, we made another comparison with a cognitive GPSR that does not consider RSUs. To accomplish this task, we simulated GPSR in combination with a scheme by Felice *et al.* [40] and refer to it as the reference scheme without RSU. The RSUs function as a backbone network to ensure connectivity for the reference scheme with RSU. An RSU helps the querying node to greedily route the packet if the node is within transmission range. When any querying node is not within the $RSU's$ transmission range, it uses the simple GPSR scheme to forward the packet. Three metrics are used to evaluate the performance of our proposed protocol: (a) end-to-end delay, (b) packet delivery ratio, and (c) routing overhead ratio.

Figures 2.5(a) and 2.5(b) show the performance of end-to-end delay in the city and highway scenarios, respectively, as a function of the number of vehicles, with different probabilities of the PU being idle as a parameter. End-to-end delay is defined as the difference between start time and end time of a packet going from source to destination. With an increasing number of vehicular nodes in the network, the delay decreases. Figure 2.5(a) shows both sparse and connected network conditions. When the network is sparse (between 15 and 20 nodes), the delay is high in both schemes. Sparse conditions occur for two reasons: the administrator may not find any reply messages due to neighboring sparse segments, or the relay node in normal mode may not find a next-hop node. If it is the former, the RSUs serve as relay nodes, but for the latter, the relay node applies a store-carry-and-forward approach, which induces delay. As both protocols consider the RSU in this scenario, the difference in delay is due to the difference in selection of the best relay node. The reference scheme selects a relay node based on distance only, whereas our proposed scheme considers message delivery time, which includes both speed and direction of vehicles. Hence, our target is to minimize the message delivery time among all the next-hop nodes between the source and destination. For that reason, our proposed scheme shows

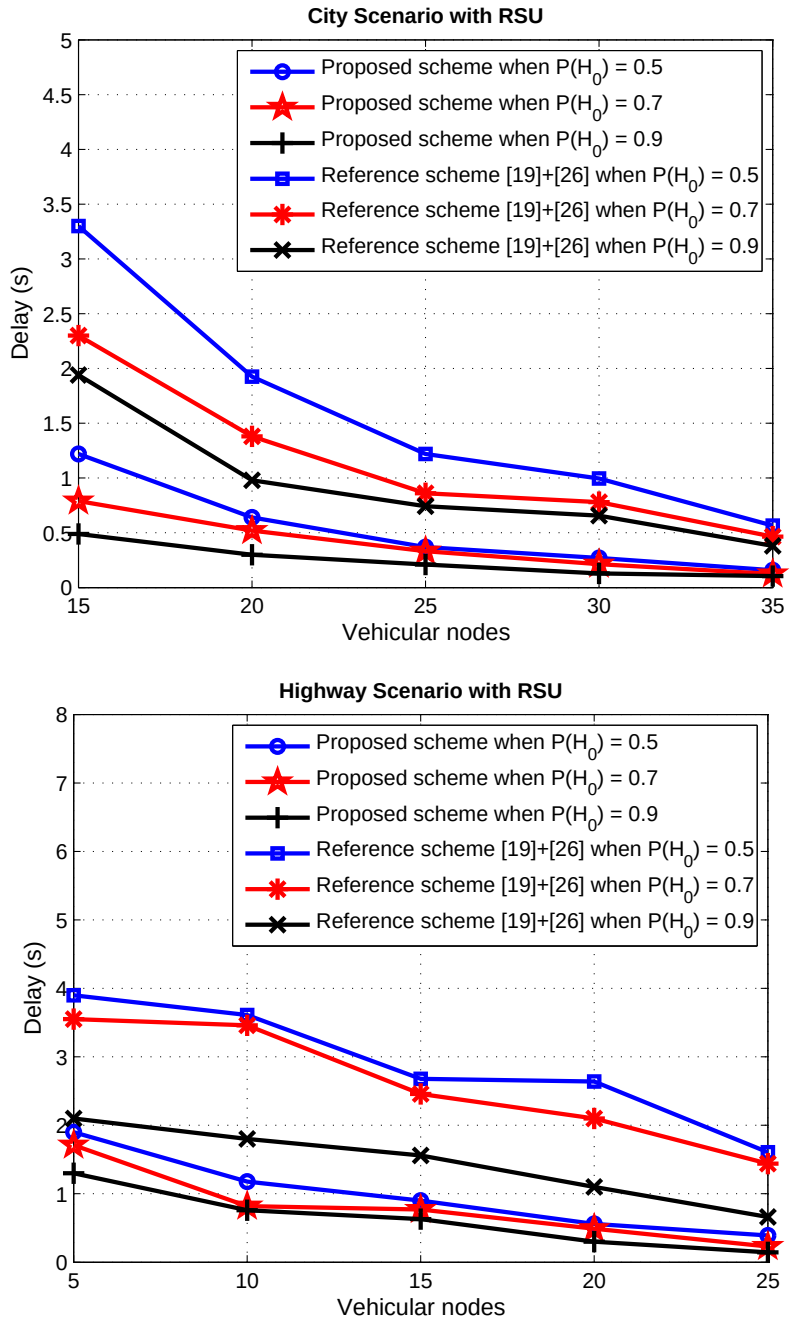


Figure 2.5: Performance comparison in terms of end-to-end delay with different probabilities of the PU being idle for: (a) city scenario and (b) highway scenario.

less delay, compared to the reference scheme under both sparse and connected network conditions. Because this is a cognitive routing scheme, the basic challenge for all the nodes

is to select at least a common idle channel to communicate with each other. Sometimes, a relay node is available within the querying node's transmission range but a channel is not free. This causes additional delay in the whole network. Another challenge in this scheme is the location of nodes under sparse network conditions. If within transmission range of an RSU, packet delivery can be done quickly and in less time, but if not, then the vehicle has to apply store-carry-and-forward which incurs additional delay in the network. As channel selection is random, we cannot achieve the least time duration or 100% delivery in our proposed scheme, even considering RSUs in the network, for the reasons described above. Figure 2.5(b) also shows that the delay in the network decreases with increasing vehicular density. As this is a highway scenario, vehicles are moving only in some segments of the road in both directions at different speeds, while other segments are sparse. Therefore, the fragility of links is high in the highway scenario. Although more channels are free on highways, compared to city scenarios, availability of a relay node cannot be assured in sparse segments of the highway. The reason for high delay in a sparse network is due to not finding an RSU within the vehicle's transmission range and/or not finding a common channel between the two communicating nodes. If a vehicle on a highway does not find a relay node or RSU nearby and within transmission range, it has to carry the packet until either it enters an RSU's transmission range or it finds another vehicle. For that reason, delay is high when the number of vehicles is between 5 and 10. Both Figs. 2.5(a) and 2.5(a) also show that decreasing the idle probability decreases network performance. The reason for the decrease is facing the difficulty in finding a common free channel when the idle probability of the PU decreases.

Figures 2.6(a) and 2.6(b) show the packet delivery ratio in the city and highway scenarios, respectively, as a function of the number of vehicles with different probabilities of the PU being idle as a parameter. Packet delivery ratio is defined as the ratio of the number

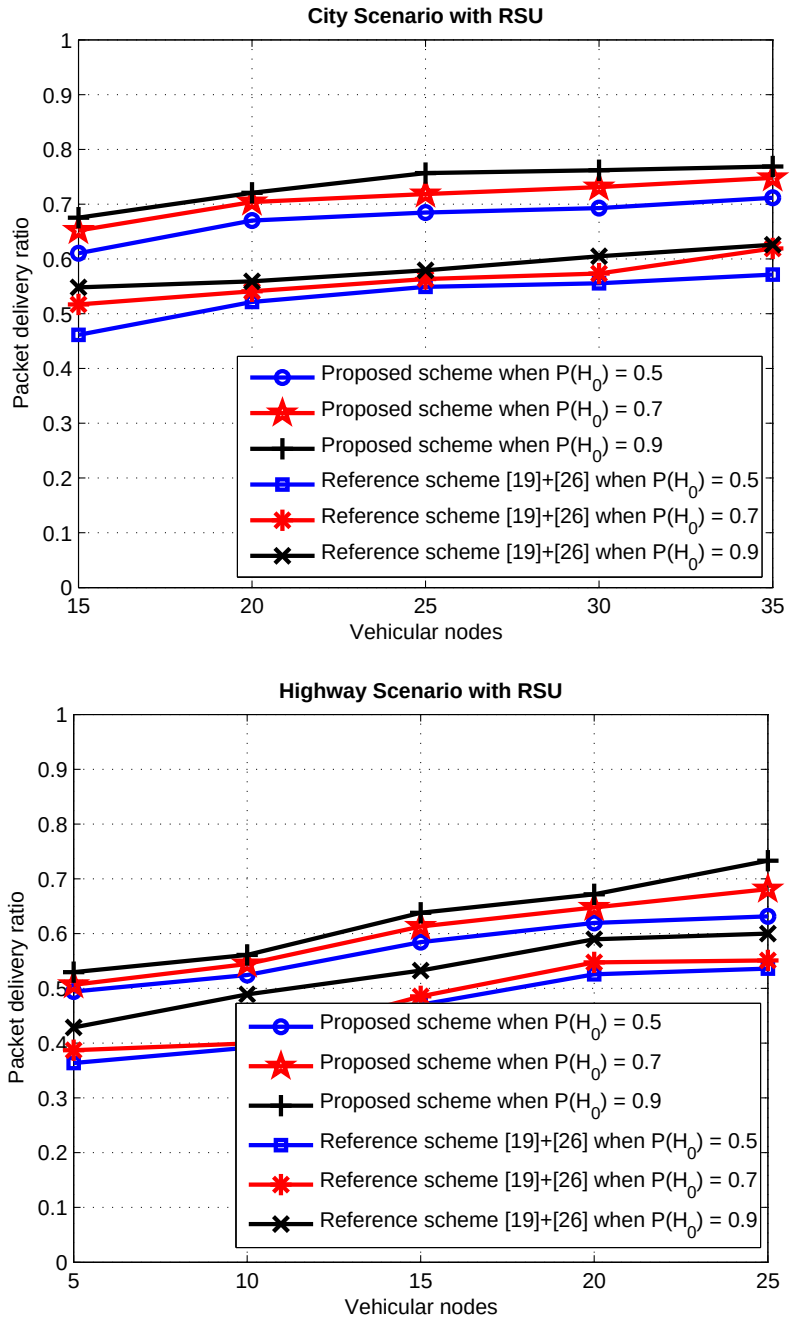


Figure 2.6: Performance comparison in terms of packet delivery ratio with different probabilities of the PU being idle for: (a) city scenario and (b) highway scenario.

of packets delivered to the number of packets generated. The packet delivery ratio for both proposed and reference schemes increases with an increasing number of vehicular nodes in

the network. When the network is sparse at a 50% idle probability for the PU, we achieved 61% successful delivery of packets in the city scenario, and 49% in the highway scenario. RSUs at junctions improve network performance, even under sparse network conditions for the city scenario. The administrator plays the key role in improving network performance due to calculating the degree of sparsity—that is, δ_{ij} in (2.11) to find busy streets—thereby avoiding a sparse network in our proposed scheme. Also, predicting the channel state for future segments helps the administrator in making a decision. Nevertheless, as vehicles are moving in both directions at different speeds, link stability is fragile in some cases due to simultaneous selection of channel and relay node. Similarly, the highway scenario makes more sporadic links due to sparse segments, which decreases the successful delivery of packets. Therefore, we achieved only 76% successful delivery of packets at maximum in the city scenario, and 73% in the highway scenario. Network performance decreases with a decreasing idle probability for the PU for the same reasons as for the difficulty in finding a free common channel. It means that the channel is occupied by the licensed user for long durations. Hence, there are fewer chances for vehicles to have a common idle channel for communicating with each other when the probability of the PU being idle decreases. In comparisons with spectrum sensing techniques, the message-passing algorithm in our proposed scheme outperforms the cooperative spectrum sensing approach of the reference scheme. The BP algorithm considers the correlation among sensing data from different vehicles, which enhances the accuracy of the hypotheses concerning spectrum availability, and the larger value of $\eta = 0.9$ yields two states, H_i and H_j, that are highly correlated. However, the reference scheme algorithm in which sensing results are stored in a spectrum table and periodically broadcast on the common control channel is limited to the range of segments for which each coordinator keeps a record of spectrum availability. Therefore, similar results can be found for packet delivery ratios in both scenarios in terms of the idle

probability for the PU. Figures 2.6(a) and 2.6(b) show that the delivery ratio outperforms the reference scheme by providing more stable paths between source and destination, especially when vehicular density and the idle probability of the PU are high. Broadly speaking, our scheme for the city scenario provides more stable paths due to having two modes: anchor and normal. Vehicles in normal mode follow the decision of the administrator/anchor vehicles. The performance in the highway scenario is slightly reduced because on a straight road vehicles do not find any other street or junction to successfully deliver the packet by avoiding a sparse network condition. Also in reality, highway roads are sparser than streets in the city scenario.

Figures 2.7(a) and 2.7(b) show the routing overhead ratio of the city and highway scenarios, respectively, as a function of the number of vehicles with different probabilities of the PU being idle as a parameter. Routing overhead ratio is defined as the ratio of the number of control packets to the total number of packets in the network. The routing overhead ratio for both the proposed and the reference scheme increases with an increasing number of vehicular nodes in the network. We observed a similarity in both city and highway scenarios in terms of an increase in overhead ratio when vehicular nodes increase and when the idle probability decreases. The higher the number of vehicles, the higher the message update rate. However, the proposed scheme outperforms the reference scheme in both scenarios. The reason for the better performance is our selection criterion that reduces the unnecessary control messages by providing updated information for each node due to cooperation among vehicles and RSUs. It can be seen from Figs. 2.7(a) and 2.7(b) that the maximum overhead ratio of our proposed scheme for the highway scenario is almost 17%, whereas for the city scenario, it is less than 10%. Furthermore, Figs. 2.7(a) and 2.7(b) also show that increasing the idle probability of the PU decreases overhead. This means that the channel is occupied by the licensed user for less time. Hence, vehicles

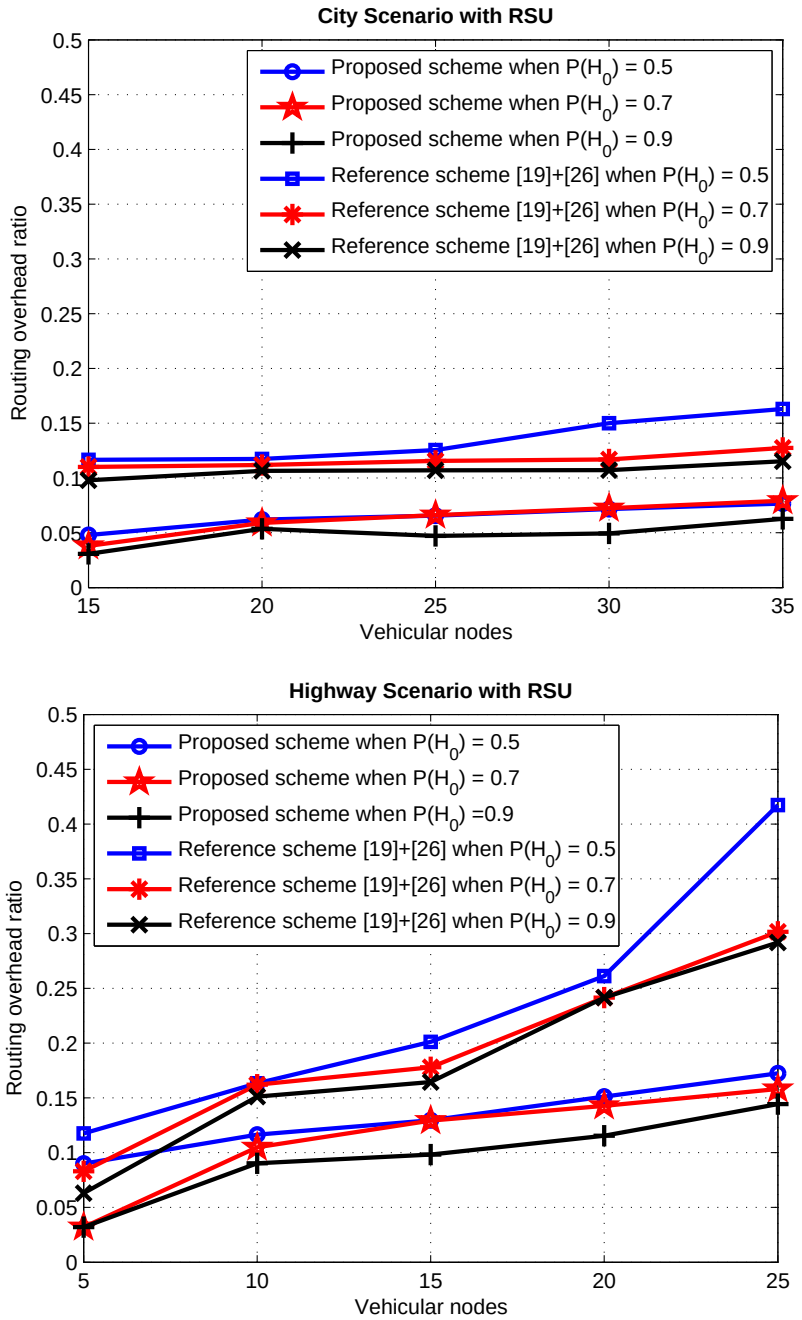


Figure 2.7: Performance comparison in terms of overhead ratio with different probabilities of the PU being idle for: (a) city scenario and (b) highway scenario.

have more chances of finding a common idle channel to communicate with each other when the probability of the PU being idle increases. Also, making a decision at the anchors

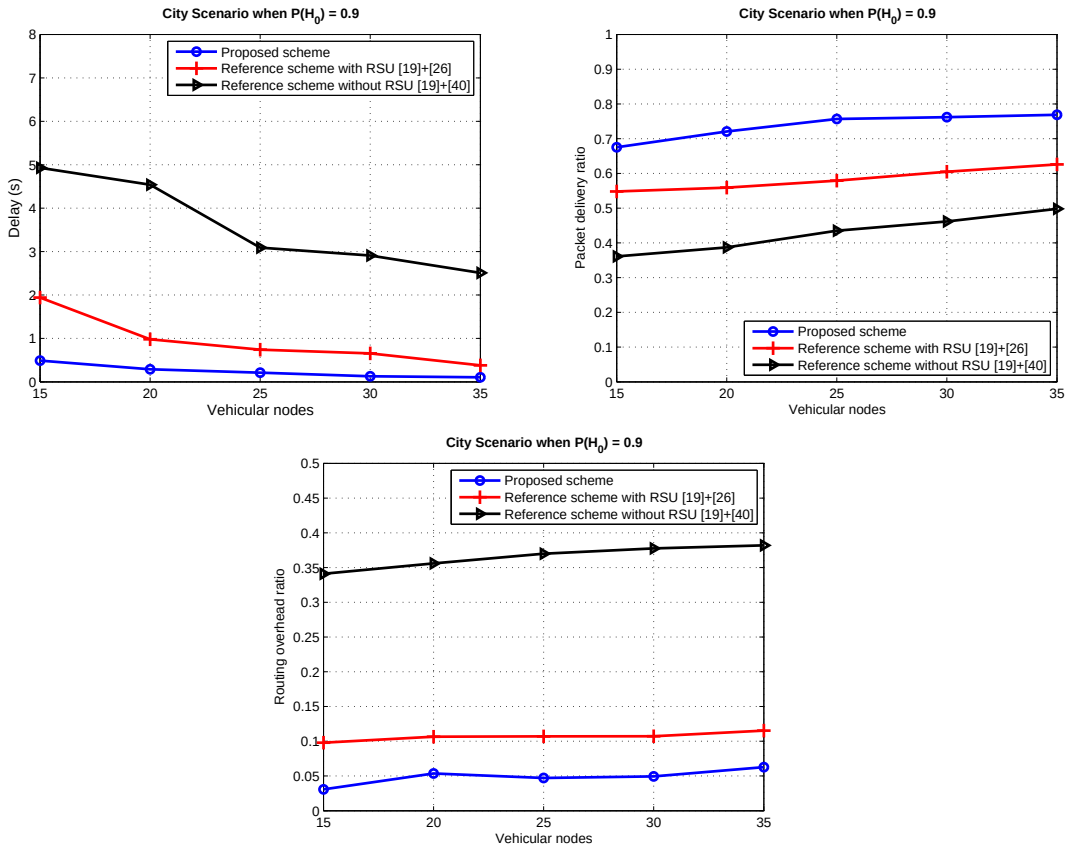


Figure 2.8: Performance comparison between RSU and non-RSU schemes for the city scenario in terms of (a) end-to-end delay, (b) packet delivery ratio, and (c) overhead ratio.

helps the querying node find the best suitable relay node in the city scenario, which reduces overall network overhead, compared with the reference scheme, therefore increasing network performance, even under sparse network conditions. The term *best* here represents the node that quickly delivers the packet to the destination and that has a common idle channel for communications. On the other hand, the highway scenario occasionally reduces sparsity by contacting a nearby RSU. A node outside communications range of an RSU in sparse segments applies the store-carry-and-forward scheme until it finds connectivity, and as a result, increases network performance in terms of routing overhead when compared with the reference scheme.

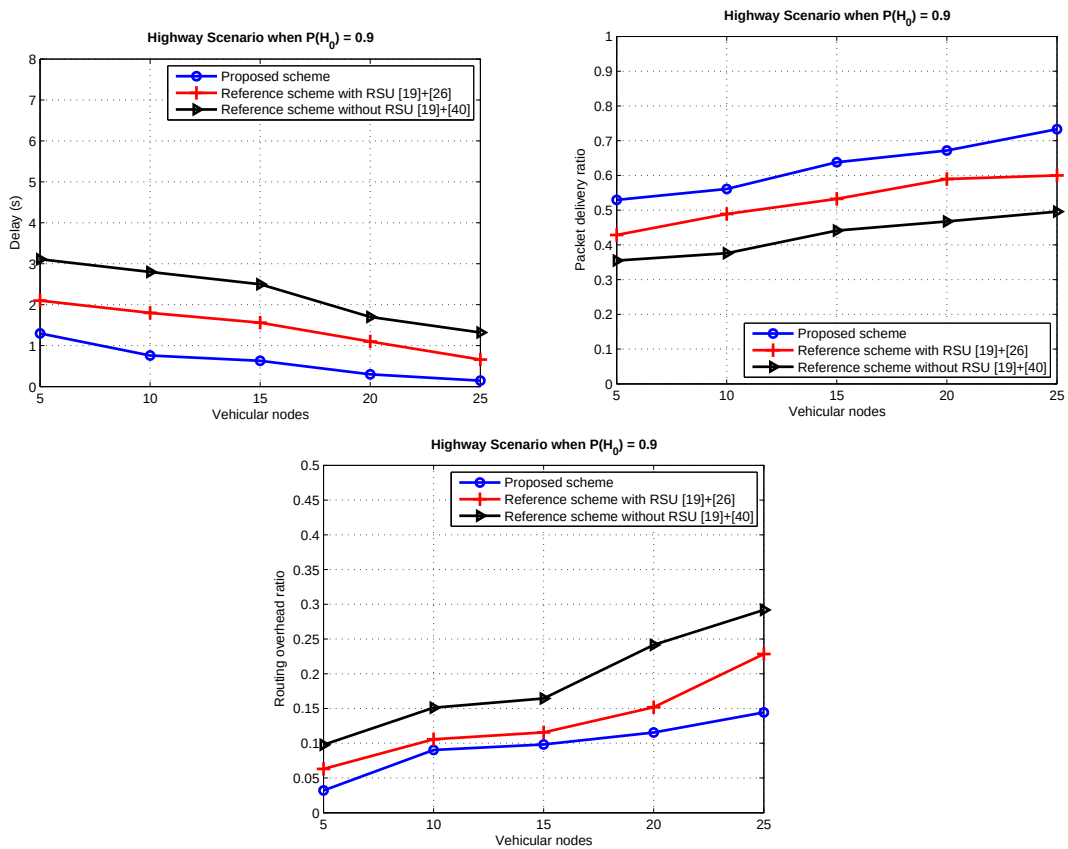


Figure 2.9: Performance comparison between RSU and non-RSU schemes for the highway scenario in terms of (a) end-to-end delay, (b) packet delivery ratio, and (c) overhead ratio.

Another set of simulation results is shown in Figs. 2.8 and 2.9. These are comparisons of the proposed and reference scheme with another scheme that does not utilize an RSU in the whole network. As mentioned earlier, we refer to it as the reference scheme without RSU. We compared these results to show the impact of utilizing an RSU for vehicular networks. As depicted in Figs. 2.8 and 2.9, our scheme for both highway and city scenarios outperforms the other schemes, even though the reference scheme with RSU outperforms the reference scheme without RSU. Hence, the network performance for the reference scheme without RSU is poorer than the other two schemes. We observed a minor change in the end-to-end delay for the reference scheme without RSU. It is clearly seen

from Figs. 2.8(a) and 2.9(a) that the delay in the city scenario is higher than in the highway scenario. The reason for the increase is the absence of an RSU, which results in the creation of longer paths and incorrect packet directions in city scenarios. Also, if a vehicle finds another node in a city scenario, it may not select it as a relay node due to not finding a common channel between the two, whereas there are fewer chances of this situation in the highway scenario due to having plenty of white space. As a result, the delay without using an RSU in the city scenario is higher than all other cases, especially when vehicular density is low. We see the same pattern of results for RSU and non-RSU schemes in Figs. 2.8(b) and 2.9(b). The delivery ratio for RSU schemes outperforms the non-RSU scheme. Figures 2.8(c) and 2.9(c) show a comparison of RSU schemes with the non-RSU scheme in terms of overhead ratio for the city and highway scenarios, respectively. The non-RSU scheme in Fig. 2.8(c) shows a large difference in overhead ratio, compared with the RSU schemes. The reason for this is considering both highly dense and sparse network conditions simultaneously, without using RSUs. A similar observation can be made for the highway scenarios for the non-RSU scheme. Therefore, it is obvious that without RSUs in the network the nodes need to exchange more messages to stay updated. Also, finding a common channel between two communicating nodes increases the message update rate in the network. GPSR does not perform well under sparse network conditions. Using RSUs in the network improves its performance, when compared with the non-RSU scheme, but its overall performance in all scenarios is still lower than our proposed scheme. Hence, we conclude that selecting a relay node based on message delivery time in a cognitive routing scheme is more stable than making a distance-based selection. The greedy approach does not predict delivery time. It may take longer to reach the destination, especially when a common idle channel is the basic criterion for communications among nodes. Therefore, our time-based prediction scheme performs better in cognitive routing networks for both

highway and city scenarios. A complete analysis of our simulated results shows that RSU schemes outperform the non-RSU scheme, and our proposed scheme outperforms the two reference schemes for both scenarios. Also, decreasing the idle probability for the PU decreases network performance. Therefore, Figs. 2.8 and 2.9 only show simulation when idle probability $P(H_0) = 0.9$. As the scheme without an RSU shows poorer performance than the RSU schemes, we can assume poorer performance of this scheme for lower probabilities; hence, we omitted the results due to space limitations.

2.4 Chapter summary

In this chapter, a novel, hybrid cognitive routing scheme for both highway and city scenarios by considering both V2V and V2I communications is proposed. The combination of both channel selection and relay selection in a vehicular communications network makes this method unique. Both dense and sparse network conditions are considered in this scheme. When a source node wants to send a packet to a destination node, it selects the best relay node based on message delivery time to find a stable path between itself and the destination. Channel selection is done using a BP algorithm with the cooperation of vehicles in order to enhance the accuracy of hypotheses concerning spectrum availability. Vehicles only communicate with each other if they have consensus about a common idle channel. The RSU serves as a storage device to enhance spectrum availability by providing channel information for future segments in advance, and it functions as a relay node under sparse network conditions. The results of this proposed scheme show better performance for end-to-end delay, packet delivery ratio, and routing overhead ratio.

Chapter 3

Cognitive Maritime Wireless Networks

3.1 Introduction

Maritime communications play an essential role in providing variety of services to users aboard. These services include ship navigation, ship traffic management, location, and all other entertainment-related information for passengers [2]. The demand for safe and stable maritime communications has been increased due to the increase in number of marine users. Existing maritime communication systems are based on high frequency (HF), very high frequency (VHF), and ultra-high frequency (UHF) radios which are currently insufficient for growing maritime requirements [7]. To fulfill the increasing needs of maritime communication systems, licensed spectrum can be used opportunistically by unlicensed users while keeping the licensed users safe [41]. A stable wireless communication link is essential for maritime communications with the availability of spectrum. Therefore, a new technique is required to provide stable link for cognitive maritime communications by ensuing coopera-

tion among marine users.

In maritime networks, ship-to-ship communication is continuously perturbed by sea waves that cause fluctuations in the signal strength resulting in fragile communication links; therefore, establishing a stable link in sea environment is a challenging task. Similarly, because of the movement of sea surface channel statistics also change continuously [12]. Furthermore, due to increasing demands of seafaring internet users, bandwidth allocations has been congested; hence, it is difficult for maritime ad hoc network to find dedicated spectrum [42]. CR seems to be a technology to alleviate this issue also in ship-to-ship communication. Ships are allowed to opportunistically sense the spectrum, provided they ensure the operation of PU is not affected. Spectrum sensing in cognitive maritime networks is in its early stages in comparison with cognitive radio networks on land. The main objective of spectrum sensing in cognitive maritime networks is similar to generic cognitive radio networks to provide spectrum opportunities to unlicensed (cognitive) users by keeping PU activity safe. Ejaz *et al.* [42] are the first to consider spectrum sensing in cognitive maritime networks. They investigated an entropy-based detection to offset the sea state effects in maritime cognitive radio network by using optimal number of samples to calculate the entropy of sensed signal as an information measure of PU presence/absence. Their results showed better performance for higher sea states with optimal number of samples but these results still do not satisfy the constraints of probability of detection and false alarm. Tang *et al.* [43] introduced the idea of cognitive radio to automatic identification system (AIS) for the first time by sensing white spaces based on energy detection scheme without interfering AIS services. They opened new doors for spectrum sensing in cognitive maritime VHF networks.

Due to rough sea surface, routing in cognitive maritime networks is more challenging as compared to conventional cognitive routing protocols on land. Apart from distinct

challenging environment in cognitive maritime networks, maritime communication is analogous to vehicular communication; therefore, few routing protocols proposed for VANETs can be applied in maritime environment. But the performance of these protocols in maritime networks is poor than vehicular networks because links in marine environment may break more frequently due to constant movement of sea surface. The proposed scheme in this chapter is applied for both flood-based and geographical routing protocols to measure the maximum duration of a route that will remain active in marine networks for communication between source and destination. A few routing protocols that have been proposed in literature are listed here. Kong *et al.* [44] proposed an aggregated-path routing approach in multi-hop wireless maritime networks. The purpose was to avoid retransmissions due to long bad duration of links in maritime communications. Their simulated results showed that aggregated-path routing is better than traditional single-path routing. A maritime two-state (MTS) routing protocol [2] was proposed for maritime multi-hop wireless networks. All ships in the network can be in one of two states: beaconing or predicting. The beaconing state is responsible for exchanging routing information with the neighboring nodes whereas the predicting state determines the future location of each ship. Their results showed better performance in terms of bandwidth utilization for coverage areas of up to 10 km. Similarly, four different MANET routing protocols have been implemented [45] using the marine environment for the coverage range of up to 40 km. A comparison was made between these protocols showing their advantages and disadvantages. These protocols have limitations in a marine environment, which can be sparse in some locations and dense in others. Among these MANET protocols, ad hoc on-demand multipath distance vector (AOMDV) was found to be efficient for ship-to-ship communication.

All of these existing routing protocols for maritime ad hoc networks do not consider spectrum scarcity issues caused by congested bandwidth allocations. Due to increasing

demand of marine users, spectrum is found to be insufficient to meet the needs of maritime communications. As the sea surface changes constantly, the links may break frequently; therefore estimation of path duration is essential for maritime ad hoc networks. Accordingly, selection of routing protocol plays an important role for estimation of path duration. For that reason, spectrum sensing and routing are important to be considered together while implementing a maritime ad hoc network. To enhance path stability in the network, we are considering both spectrum scarcity and routing issues together. The aim of this chapter is to find a stable path between source and destination based on BP algorithm for cognitive maritime multi-hop ad hoc network. BP algorithm [31], an iterative message passing algorithm can also be applied in maritime communications for collaborative spectrum sensing. This algorithm allows each ship to send the local sensing results obtained from energy detection scheme to all the neighbors in its communication range. Then, each ship combines its belief with the beliefs of all its neighbors to make a final belief about the existence of PU. Ships update each other periodically about their current positions, and the *Kalman* filter is used to predict their future positions. Finally, the best stable path is selected using two well-known routing protocols by finding minimum link duration between source and destination with their beliefs: one is flood-based routing protocol named ad hoc on-demand distance vector (AODV) [46] and the other is geographical routing protocol named GPSR [19].

The remaining chapter is organized as follows. In Section 3.2, we propose the belief propagation-based ad hoc routing algorithm. Section 3.3 demonstrates performance results, and, finally, Section 3.4 concludes the chapter.

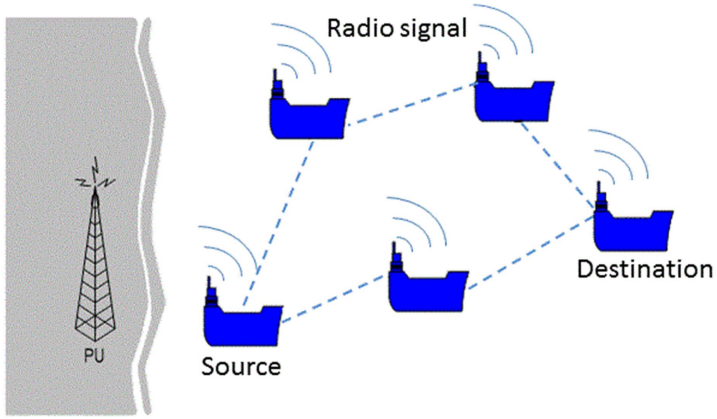


Figure 3.1: Cognitive maritime multihop ad hoc network.

3.2 System model and the proposed scheme

We consider a cognitive maritime ad hoc network with I ships, which is represented by a graph where each node represents a ship and each edge is a communication link between two ships as shown in Fig. 3.1. A cognitive routing technique is proposed by considering the movement of ships in marine environment. The purpose of using cognitive principles in maritime ad hoc network is to increase the spectrum opportunities for ship-to-ship communication. This is a spectrum-aware routing scheme in which collaborative spectrum sensing is done by using BP algorithm, and then a route is selected based on both AODV and GPSR routing protocols. Our goal is to find a stable path among all the paths between source and destination which maximizes the path duration to facilitate communication between different ships.This path is calculated by combining beliefs and link durations for total number of hops between source and destination.

Ships are assumed to be equipped with GPS receiver to get its current location. All ships periodically update current geographic positions of their neighborhood ships and

further predict their future positions using the *Kalman* filter, which will be described in Section 3.2.2.1. This helps the querying node (e.g., source node in Fig. 3.1 to find the best relay node that makes stable path between source and destination by considering the current and future positions of all the nodes in its communication range. Primary users are assumed to be sited close to seashore as shown in Fig. 3.1. We define PUs as incumbent users that provide services for transmission of important information like vessel navigation, disaster rescue, weather broadcasting, and so on. We also assume that there is plenty of white space (WS) available at sea as analyzed in [12] and we divide the TV band into channels where PU activity is modeled as exponential on/off activity pattern. Spectrum sensing is done by energy detection scheme. Each ship senses the spectrum using a binary hypothesis model which is defined as follows:

$$x_i(t) = \begin{cases} n_i(t), & H_0 \\ s_i(t) + n_i(t), & H_1 \end{cases} \tag{3.1}$$

where $i = 1, 2, ..., I$, $s_i(t)$ is the complex PU signal received by ship i, and $n_i(t)$ is complex additive white Gaussian noise. Therefore, in a discrete domain, the energy-based test statistic is given as follows:

$$x_{E_i} = \sum_{n=1}^{N} x_i[n]\tilde{x}_i[n] \tag{3.2}$$

where N is the time-bandwidth product, and $\tilde{x}_i[n]$ is the conjugate signal of $x_i[n]$.

Generation of a sea environment is a challenging task. Pierson Jr. and Moskowitz [47] describe the movement of sea waves by dividing sea states into 10 levels. Sea state is a measure of sea surface movement using significant wave height, wave period, and wave length as parameters. Each sea state has its own wave height, average period, and average wave length. Sea movement changes the orientation of an antenna, which affects the received signal power. We assume that all antennas are omnidirectional in the horizontal plane, even

though, due to the movement of the sea surface, tilting of antenna masts causes a change in antenna gain that affects the received signal′s power. Therefore, different ships experience a different signal-to-noise ratio (SNR), which is calculated as follows:

$$\gamma_i = \frac{P_{R_i}}{N_o W} \tag{3.3}$$

where $N_o W$ is the total noise power, and P_{R_i} is the received power calculated as follows:

$$P_{R_i} = P_T - PL \tag{3.4}$$

P_T and PL are transmitted power and path loss, respectively. For the maritime environment, path loss PL is a function of frequency f and sea surface height h, and was defined by Timmins and O′Young [48] as follows:

$$PL(h, f) = PL(d_o) + 10 + [(0.498log_{10}(f) + 0.793)h + 2]log_{10}\left(\frac{d}{d_o}\right) + X_f \tag{3.5}$$

$PL(d_o)$ is the path loss measured at a reference distance from the transmitter, and X_f is a Gaussian random variable with zero mean and standard deviation, given as $\sigma_f = [0.157f + 0.405] \times h$.

The proposed method is twofold: first, the selection of free channel where collaborative spectrum sensing is done using belief propagation algorithm by exchanging the local decisions between neighboring ships to make a final belief and, second, the selection of a stable path by finding minimum link duration between source and destination with their beliefs which in turn maximizes the path duration. In the following sections, we discuss these two parts thoroughly.

3.2.1 Channel selection scheme based on belief propagation algorithm

We consider cognitive ship-to-ship communication in which all nodes are moving ships. Each ship periodically senses the spectrum and stores the result in its sensing table. BP [31] is an

iterative algorithm in which messages are exchanged to approximate the marginal probabilities (i.e., the beliefs).The first step for BP algorithm is to calculate the local information which is equal to the a posterior probability. We use energy detection scheme for local sensing as discussed in (3.1) and (3.2) above. For each ship i, the a posterior probability is calculated as follows:

$$\varphi_i^f(H_h) = P(H_h|x_i) = \frac{P(x_i|H_h)P(H_h)}{P(x_i)} \tag{3.6}$$

where $f \in M$, $P(x_i|H_h)$ is the probability density function of normally distributed complex random variable x_i conditioned on H_h, $(h = 0, 1)$. $P(x_i)$ is a normalizing constant, and $P(H_h)$ is the prior probability, which is assumed to be constant for all ships. Each ship exchanges its local sensing results with all its neighboring ships and updates its sensing table according to BP algorithm. Two ships i and j in the communication range of each other exchange their messages as follows:

$$\mu_{ij}^f(H_j) = w \sum_{H_i} \psi_{ij}^f(H_i, H_j)\varphi_i^f(H_i) \prod_{k\in(N_i-\{j\})} \mu_{ki}^f(H_i) \tag{3.7}$$

$\mu_{ij}^f(H_j)$ describes the belief about the state of ship j as estimated by ship i, w in (3.7) is the weighting factor, the term $k \in (N_i - j)$ describes how k only belongs to the neighbors of i and not to the neighbors of j, and $\psi_{ij}^f(H_i, H_j)$ is a compatibility function which depends on the correlation between states H_i and H_j. The compatibility function is defined as follows:

$$\psi_{ij}^f(H_i, H_j) = \begin{cases} \eta & if\ H_i = H_j \\ 1-\eta & if\ H_i \neq H_j \end{cases} \tag{3.8}$$

Finally, the belief of each ship is calculated as follows:

$$b_i^f(H_i) = w\ \varphi_i^f(H_i) \prod_{k\in(N_i)} \mu_{ki}^f(H_i) \tag{3.9}$$

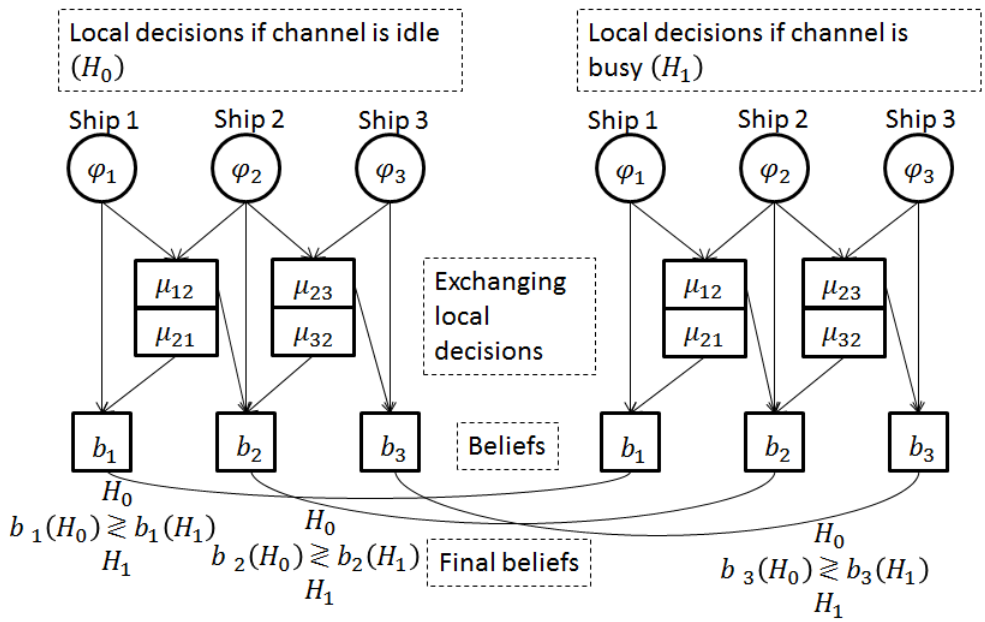


Figure 3.2: An example illustrating belief propagation algorithm for collaborative spectrum sensing.

On the basis of these beliefs, each ship makes the final decision about the current channel on which it is moving as follows:

$$D_i^f = \begin{cases} H_0 & if\ b_i^f(H_0) > b_i^f(H_1) \\ \\ H_1 & if\ b_i^f(H_0) < b_i^f(H_1) \end{cases} \tag{3.10}$$

An example illustrating how three ships exchange their individual observations resulting from energy detection scheme using belief propagation algorithm and then make the final belief about state (idle/busy) of channel is shown in Fig. 3.2.

3.2.2 Routing scheme based on estimation of path duration

The estimation of path duration in cognitive maritime communications makes the routing efficient by exchanging geographic positions and beliefs of each ship with their neighboring ships. In this subsection, we explain how stable path is calculated by using beliefs obtained

in the previous subsection. As this is cognitive ship-to-ship communication, the position of ships and channel condition are changing continuously with the movement of sea. All ships send messages to their neighboring ships about their positions and beliefs which are considered as additional entries in a beacon message. Therefore, each ship can calculate its distance from its immediate neighbors. We use the *Kalman* filter to predict future positions of all the ships. We will discuss in Section 3.2.2.1 how we estimate the future values of position and velocity of ships by using the *Kalman* filter algorithm.

The estimation of path duration is helpful in selecting the path to transfer data packets from source to destination. An efficient routing protocol is required to estimate the path duration considering the challenges faced by marine environment. A few of existing routing protocols for terrestrial environment have been implemented in marine environment [45] and also some new routing protocols have been proposed for marine communications [2, 44]. We are concerned with the estimation of path duration to select a stable route for ship-to-ship communication as maritime link might be blocked by various propagation impairments.Therefore, we use both flood-based and geographical routing protocols to check their validity among challenges of maritime environment.

To find a stable path between source and destination using AODV [46], a route request (RREQ) is sent by the source node to all the neighbors in its communication range moving towards the destination. It is noteworthy that beliefs are updated as an additional entry among all the fields of RREQ. The RREQ passes through several nodes forming active links and then finally reaches the destination. Once the RREQ reaches the destination, the destination sends back a route reply (RREP) to the source node. Hence, the stable path is calculated by computing the minimum link duration among all the links between source and destination for the common free channels, while GPSR [19] uses greedy forwarding to select next hop in making links with the source node. Three basic entities are used in

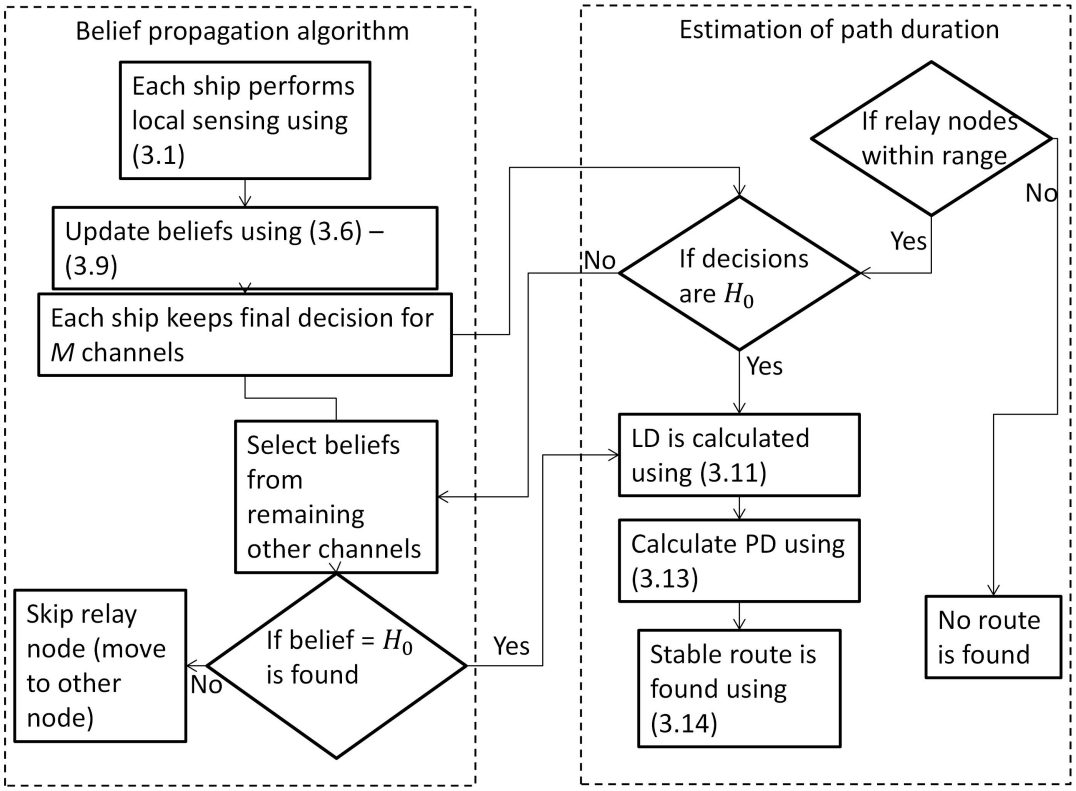


Figure 3.3: A flowchart representing proposed algorithm.

applying greedy forwarding: the position of querying node, the position of all neighbors, and position of destination. The principle says that the source node selects that neighbor node which is the closest to the destination. Again, we mention here that in selecting the next node using GPSR all nodes send their beliefs as an extra entity in beacon message. Figure 3.3 explains the comprehensive algorithm by showing how source/relay selects the next hop nodes and beliefs of free channels jointly to reach the destination and then chooses the final route which maximizes the path duration among all the paths. Two ships which are in the transmission range of each other having at least a common free channel calculate

their link duration as follows:

$$LD_{ij} = L_{ij}.min\Big(b_i^f(H_0), b_i^f(H_0)\Big), \tag{3.11}$$

where L_{ij} is the estimated time for which the direct link between two nodes within the transmission range of each other is active and is calculated in the same way as proposed by Liu *et al.* [29]:

$$L_{ij} = \frac{R \pm d_{ij}}{V_{ij}} \tag{3.12}$$

where R is the transmission range of ship i, d_{ij} is the distance between ship i and ship j, and V_{ij} is the velocity of the ships.We will explain with examples the evaluation of L_{ij} in Section 3.3. Hence, the path duration between source and destination is calculated as follows:

$$PD_p = min(LD_1^p, LD_2^p, ..., LD_{T_h}^p) \tag{3.13}$$

where T_h is the total number of hops between source and destination, p is index for path between source and destination, and p is from $1, ..., P$. Finally, a route $\hat{p}$ is selected which maximizes path duration among all the paths p:

$$\hat{p} = max_{\hat{p} \in p}(PD_p) \tag{3.14}$$

3.2.2.1 Kalman filter algorithm

As discussed in previous subsection, in order to make routing efficient by achieving a reasonable delay, we use a *Kalman* filter in our proposed routing scheme to predict future positions of all ships. In this subsection, we briefly explain the *Kalman* filter [49] algorithm.The *Kalman* filter has two vectors: state vector and measurement vector. The state vector consists of position P_t and velocity V_t of a ship; that is, $u_t = \begin{bmatrix} P_t \\ V_t \end{bmatrix}$. The measurement vector is a measurement at time t. Two equations are used in this algorithm: a process

equation and a measurement equation. The process equation predicts the future values of the ships at time $t+1$ and the measurement equation gives the observation value from the GPS. The process equation and measurement equation are defined by (3.15) and (3.16), respectively, as follows:

$$u_{t+1} = Au_t + \varepsilon_u, \tag{3.15}$$

$$z_t = Hu_t + \varepsilon_z, \tag{3.16}$$

where A and H are state transition and measurement matrices, respectively, ε_u is process noise, and ε_z is measurement noise. Both noises have a normal distribution with zero mean and a covariance matrix of Q and R, respectively.

To measure the predicted and new values of moving ships, the algorithm is further divided into two steps: a prediction step and an update step. The prediction step predicts the state and covariance whereas the update step is a combination of predicted state and observation value. The predicted values are defined as follows:

$$\begin{aligned} \hat{u}_{t+1} &= Au_t, \\ P_{t+1} &= AP_tA^T + Q. \end{aligned} \tag{3.17}$$

And the new estimated values of each ship are defined as follows:

$$\begin{aligned} \hat{u}_{t+1|t+1} &= \hat{u}_{t+1|t} + K[z_{t+1} - H\hat{u}_{t+1|t}], \\ P_{t+1|t+1} &= P_{t+1|t} - K(R + HP_{t+1|t}H^T)K^T, \end{aligned} \tag{3.18}$$

where K is the *Kalman* gain calculated from

$$K = P_{t+1|t}H^T[R + HP_{t+1|t}H^T]^{-1}. \tag{3.19}$$

Therefore, from the above equations, we can estimate the future values of position and velocity of ships by using the *Kalman* filter algorithm.

3.3 Simulation results and discussion

We evaluate the performance of proposed scheme described in this chapter in MATLAB. In this scheme, randomly placed ships are moving with various speeds up to the maximum speed of 50 km/h [2], each having a transmission range of 15 km. The variable I is varied from 5 to 20 and spectrum band is divided into $M = 2$ channels. The transmission power $P_T = 25$Watts and η can be any value between 0.5 and 1. The larger the value of η, the more the correlation between neighboring ships. Likewise previous chapter, we again assume $\eta = 0.9$ which means the two states H_i and H_j are highly correlated hence yielding large probability for $H_i = H_j$. The path loss model described in (3.5) is used for simulation. Moderate sea state having wave height between 1.83m and 2.29m [47] is used primarily to evaluate the average path duration. Average path duration is defined as the average time for which a route is active between source and destination. Random values of wave height are generated for single iteration.Therefore, the value of SNR for each ship changes continuously. Our simulation results are the average of more than 50 runs. As we are testing our scheme for two routing protocols, therefore, for simplicity, we denote our proposed scheme as flood-based Cog-SANET (acronym of cognitive ship ad hoc network) when AODV is the routing protocol and geographical Cog-SANET when GPSR is used. We evaluate the expected path duration maximized routing (EPDM-R) [29] algorithm in marine environment to compare it with our proposed flood-based Cog-SANET scheme and named it as classic Cog-SANET for simulations. Classic Cog-SANET selects the route with maximum expected path duration among all attainable paths. This routing algorithm is similar to AODV in which freeway mobility model is used and behavior of PU is calculated using call-based model.This algorithm was initially proposed for CR-VANETs; we plot it in marine environment just for a reference.

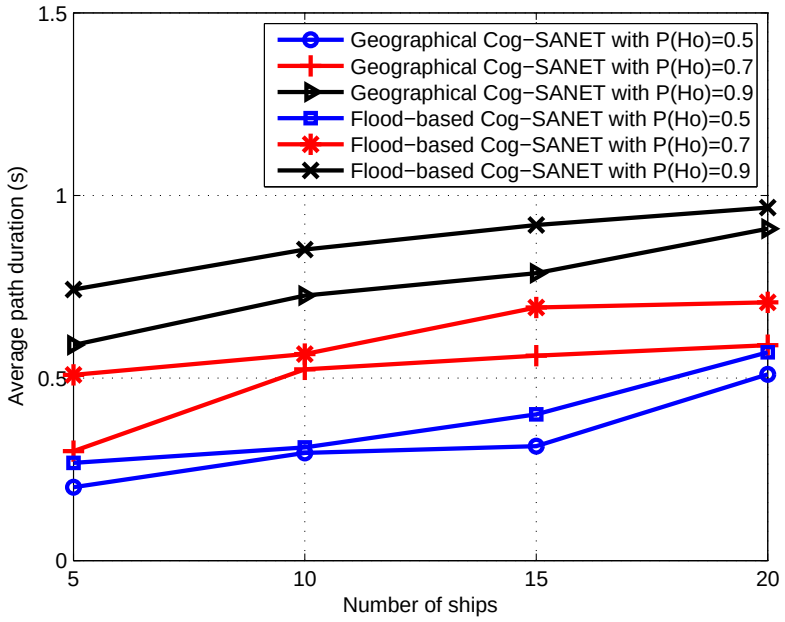


Figure 3.4: Performance comparison between flood-based Cog- SANET and geographical Cog-SANET for average path duration as a function of number of ships with different probabilities of PU being idle as a parameter.

Figure 3.4 shows the average path duration as a function of number of ships with probabilities of PU being idle as a parameter. The path duration increases with an increase in I, the number of ships. The reason for increase is the connectivity in the network due to increase in number of ships. Flood-based Cog-SANET performs better than geographical Cog-SANET when intermediate ships are moving freely in any direction in the network while source and destination are moving in the same direction. Flood-based Cog-SANET floods the RREQ to all the nodes in the transmission range of the querying node, therefore, making the links with each neighboring node it reaches the destination. The network has more paths to destination as compared to geographical Cog-SANET that makes the link only with the farthest node towards destination. Hence, flood-based Cog-SANET exhibits more stable paths as ships may remain in one′s transmission range for longer time, whereas

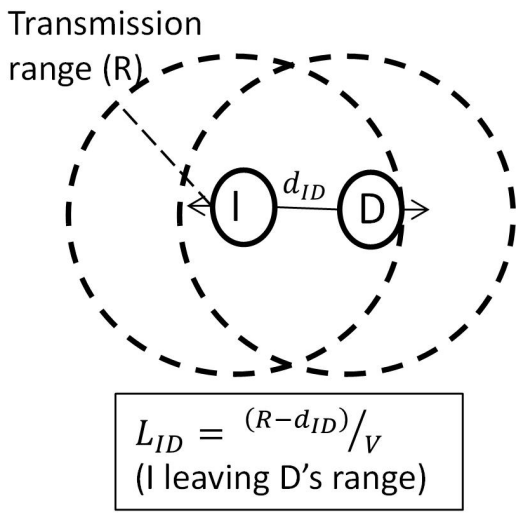


Figure 3.5: An example illustrating that the farthest node when moving in opposite direction decreases duration of link.

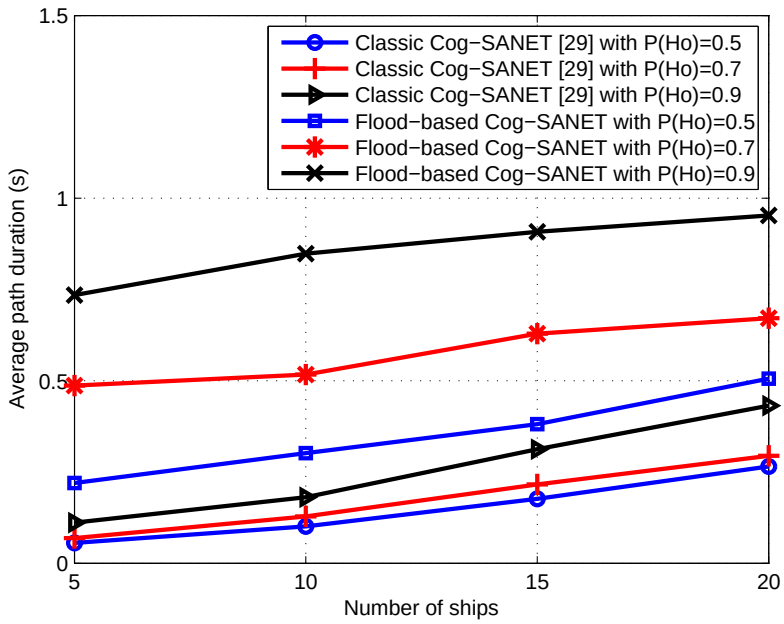


Figure 3.6: Performance comparison between flood-based Cog-SANET and classic Cog-SANET for average path duration as a function of number of ships with different probabilities of PU being idle as a parameter.

geographical Cog-SANET makes shorter routes with short duration when intermediate ships are moving in opposite direction to the destination. Also, link stability depends on the distance between two moving nodes; as the separation increases (when nodes are moving in opposite direction from destination), the path duration decreases. An example is shown in Fig.3.5. Figure 3.4 also shows that as the probability of PU being idle decreases, the performance of path duration decreases.The reason for decrease is facing difficulty in finding common free channel with decrease in probabilities. Hence, by increasing the number of ships and the probability that PU is idle, we increase the stability of the paths in the network.

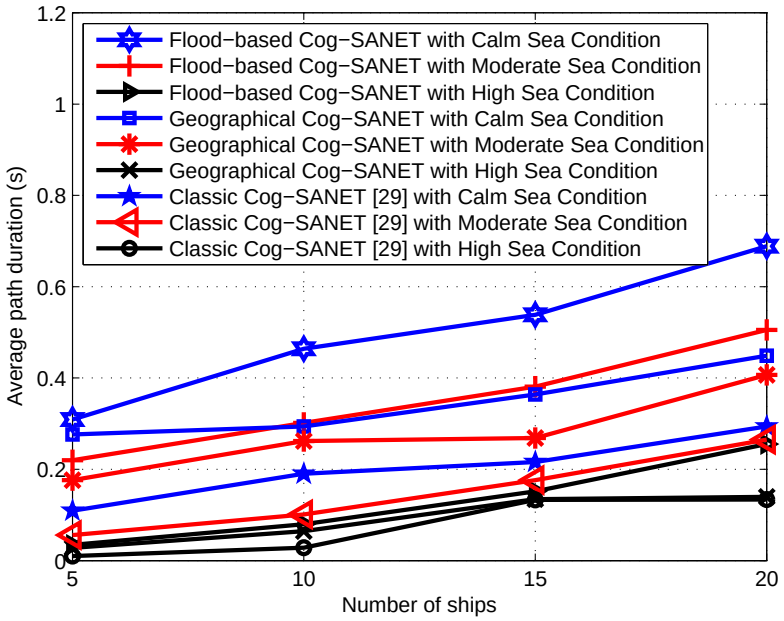


Figure 3.7: Performance comparison between Cog-SANET and classic Cog-SANET for average path duration as a function of number of ships with sea states as parameter.

Figure 3.6 shows the performance comparison of our flood-based Cog-SANET protocol with classic Cog-SANET. Classic Cog-SANET is also flood-based routing protocol proposed for cognitive VANETs; therefore, we do not compare it with geographical Cog-

SANET. By considering collaborative spectrum sensing to select a free channel for communication and by predicting future positions of all the ships, our scheme outperforms classic Cog-SANET. Fig. 3.7 shows performance of average path duration as a function of number of ships with different sea conditions as a parameter. We generate random values of wave height for calm (sea states 0-3), moderate (sea states 4-5), and high (sea states 6 and above) sea conditions as described by Pierson Jr. and Moskowitz [47] in their model and evaluate the performance of all three protocols for different sea states when ships are moving freely in any direction in the network. It can be seen from Fig.3.7 that higher sea states increase wave occlusion which occluded the link. The wave height h in (3.5) degrades the performance of whole network by rapidly increasing the path loss. An increase in h blocks the communication link between two ships which breaks the established route between source and destination.Therefore, the path duration decreases with an increase in wave height. We can also see from Fig. 3.7 that flood-based Cog-SANET outperforms the other two routing protocols due to the same reason explained above. Evaluating this metric, we conclude that wave height h causes significant impact on the overall performance.

Figure 3.8 shows an exceptional case to test the performance of both flood-based and geographical routing protocols. A comparison is made between flood-based Cog-SANET and geographical Cog-SANET for average path duration when all intermediate ships are moving in the same direction to destination. Geographical Cog-SANET performs better than flood-based Cog-SANET because of the selection of an intermediate node which is the closest to the destination.Therefore, geographical Cog-SANET makes shorter routes with long link durations which in turn increase the path duration. GPSR always selects the further distanced node closer to the destination [19] while AODV not always makes paths with this farthest node. Broadly speaking, when all the ships are moving in the same direction, the chance for each node to stay in the communication range of its next

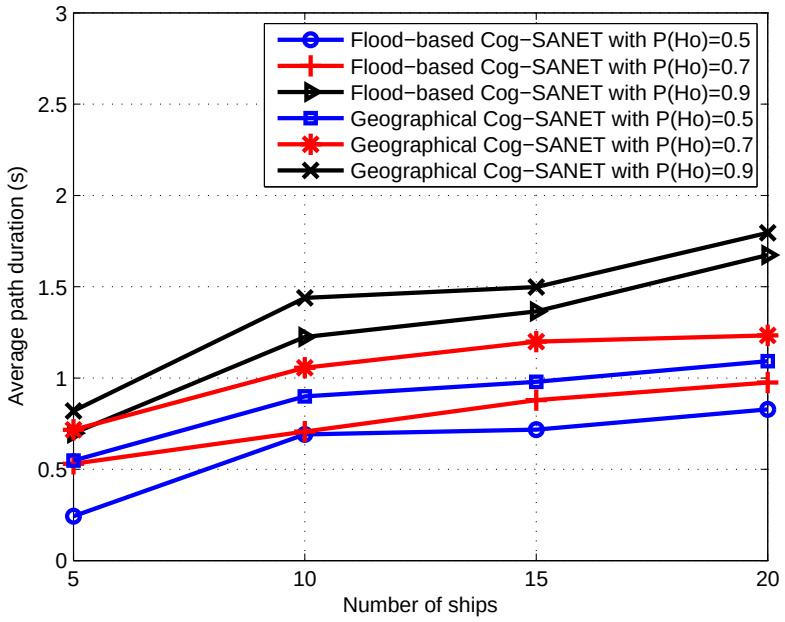


Figure 3.8: Performance comparison between flood-based Cog-SANET and geographical Cog-SANET for average path duration when all ships are moving with the same direction.

node is increased (an example is shown in Fig. 3.9. But this link may not be a stable link as it increases the chance of link breakage when any farthest node moves away from the transmission range of its previous node. Also, path duration increases with an increasing number of ships because it increases the chance for source/relay node to have more ships at the border line of one′s transmission range. This in turn increases the chance to form a link with the farthest node from source/relay node which increases the path duration.

Figure 3.10 shows the packet delivery ratio of the flood-based Cog-SANET, geographical Cog-SANET, and classic Cog-SANET for idle probability of PU, $P(H_0) = 0.9$. Fig. 3.10 shows that the delivery ratio increases with an increase in the number of ships. We achieve 89% packet delivery for flood-based Cog-SANET when there are more ships because there are more links between source and destination as compared to geographical Cog-SANET. In geographical Cog-SANET, when source/relay node finds the farthest node

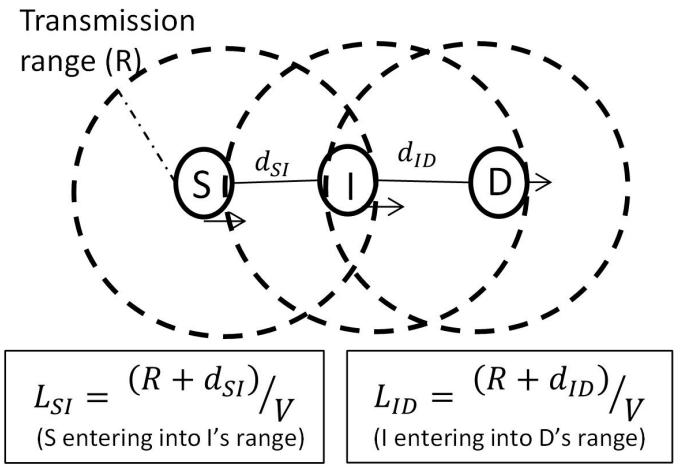


Figure 3.9: An example illustrating the farthest node when moving in the same direction with source and destination.

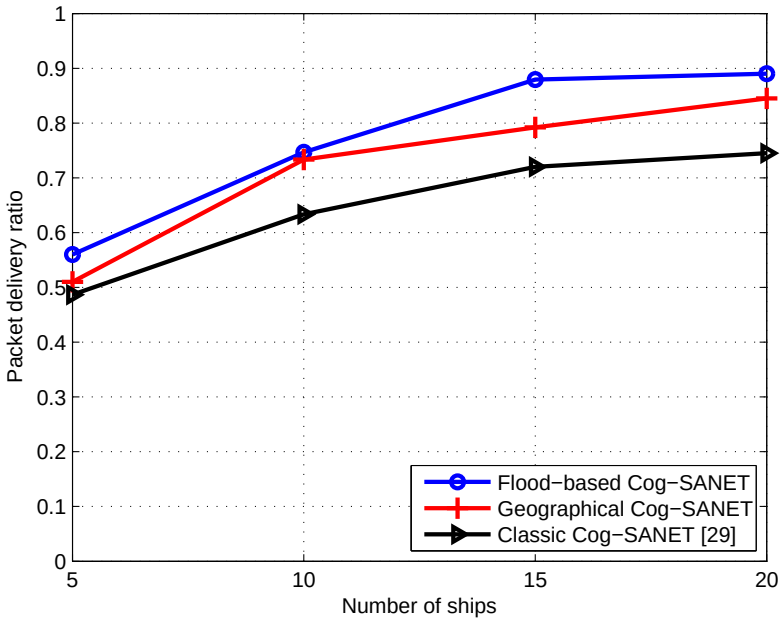


Figure 3.10: Performance comparison between flood-based Cog-SANET, geographical Cog-SANET, and classic Cog-SANET for packet delivery ratio.

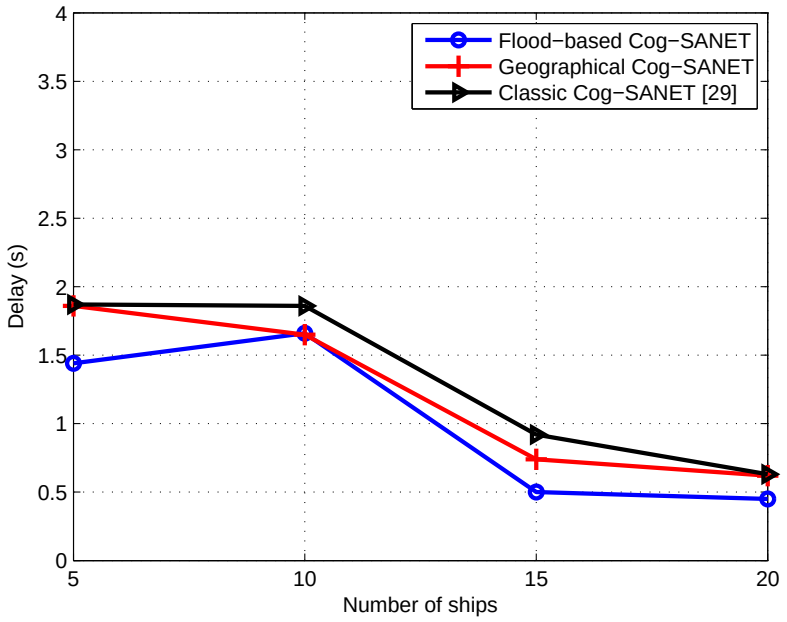


Figure 3.11: Performance comparison between flood-based Cog-SANET, geographicalCog-SANET, and classicCog-SANET for end-to-end delay.

towards destination but does not find common free channel, the packet will be dropped, while in flood-based Cog-SANET, there are other links available in the routing table of each node. Therefore, flood-based Cog-SANET outperforms the other two routing protocols. Furthermore, by considering the collaborative spectrum sensing and by predicting the future positions, both flood-based Cog-SANET and geographical Cog-SANET outperform the classic Cog-SANET.

Figure 3.11 shows the performance of end-to-end delay for flood-based Cog-SANET, geographical Cog-SANET, and classic Cog-SANET. In cognitive marine environment, in addition to sea conditions and network connectivity, another factor that affects the performance of end-to-end delay is the selection of a common idle channel. As the number of ships increases, end-to-end delay decreases due to increase in connectivity. For less number of ships, the network is sparse; therefore, nodes spend more time in making connection

with relay nodes to reach the destination. Both flood-based Cog-SANET and geographical Cog-SANET outperform classic Cog-SANET due to the same reasons explained above.

3.4 Chapter summary

In this chapter, a novel scheme for cognitive maritime ad hoc networks is proposed. The combination of both channel selection and path selection makes this method unique. Channel selection is done by the cooperation of maritime users using BP algorithm and selection of path is achieved by two well-known routing protocols AODV and GPSR to test the validity of the proposed protocol in both flood-based and geographical routing protocols. This is ship-to-ship cognitive routing technique in which a stable path is established between source and destination by combining beliefs of maritime users with their corresponding link durations for total number of hops between source and destination. The results show that AODV outperforms GPSR in all cases except the one when all ships are moving with the same direction to the destination (an exceptional case). Moreover, this scheme shows better performance for average path duration when the sea state is calm and when ship density is high in the network. This work is valid only for maritime users above the sea surface. In the next chapter, we extend this work for underwater communications.

Chapter 4

Cognitive Acoustic Underwater Sensor Networks

4.1 Introduction

Underwater acoustic communications systems have been attracting significant interest in the last decade in order to deal with various applications for scenarios ranging from the depths of the ocean to the surface of the ocean. These applications include underwater resource exploration, environmental monitoring, target tracking, oceanography data collection, ship navigation, ship traffic management, and marine animal study [2–5]. Unique challenges in the underwater environment (e.g. severe path loss, limited bandwidth, long propagation delays, etc.) and co-location of diverse acoustic communication systems in the ocean increase the demand for safe and stable communications in this new research venue. The communication systems include both natural acoustic systems (e.g. marine mammals) and artificial acoustic systems (e.g. sonar systems). They both rely on acoustic waves for communication. Luo *et al.* [8] showed that the spectrum band from 1 to 40 kHz

is heavily shared among different acoustic users, triggering high competition to utilize the spectrum resource efficiently. Like the terrestrial radio spectrum [50], maritime communication systems [51] have also undergone spectrum scarcity due to the emerging demands of underwater applications.

To alleviate the spectrum scarcity in underwater networks, cognitive acoustic (CA) is a viable solution as it can utilize a spectrum in an environmental-friendly manner (i.e. avoiding harmful interference with natural acoustic systems) and in an efficient manner (i.e. high spectrum utilization) [10]. Underwater cognitive acoustic network (UCAN) systems perform the same task of allocating an idle channel to CA users while protecting PU activity. A stable acoustic link is essential for communicating with different acoustic users in order to meet the increasing demands of underwater applications. A link is formed only when two communicating users have consensus about a common idle channel. Therefore, a new cognitive routing protocol is required to ensure cooperation among acoustic users; thereby retaining a stable link for underwater communications.

Routing in UCANs is more challenging, compared with conventional routing protocols in underwater sensor networks. Conventional routing protocols proposed for terrestrial communications have been modified for underwater communications by considering the characteristics of underwater channels. Yan *et al.* [52] proposed depth-based routing (DBR) for underwater sensor networks to provide scalable and efficient services for dense networks. DBR is based on a greedy algorithm in which each sensor node takes a decision by comparing its own depth with the depth of the previous node. The protocol achieved a 95% packet delivery ratio without considering recovery algorithms to avoid the void. Pressure routing for underwater sensor networks [53] addressed the local maxima by maintaining a recovery route. To select a set of forwarding nodes that maximizes greedy progress and limits co-channel interference, an opportunistic routing mechanism and a dead end recovery method

were used. Pompili *et al.* [54] proposed two distributed geographic routing algorithms for delay-insensitive and delay-sensitive applications in underwater environments. They investigated the problem of data gathering by achieving high acoustic channel efficiency and limiting the packet error rate.

Noh *et al.* [55] proposed void aware pressure routing (VAPR) for underwater sensor networks. VAPR is a soft-state protocol that uses enhanced beaconing to propagate the data from sonobuoys to sensor nodes, and opportunistic directional data forwarding then builds a directional trail to the closest sonobuoy. The algorithm is robust to network dynamics and ensures loop-freedom for mobile networks. Coutinho *et al.* [56] recently presented detailed guidelines for opportunistic routing protocols in underwater networks and discussed the advantages and disadvantages of candidate set selection for sender-side-based, receiver-side-based, and hybrid procedures. Carlson *et al.* [57] designed a reactive, linkstate mobile ad hoc network routing protocol – a location-aware source routing (LASR) protocol that considers the characteristics of underwater acoustic networks. LASR uses the key idea of the dynamic source routing (DSR) protocol by considering source routes for communication between autonomous underwater vehicles (AUV), maintaining only those routes that are in use. Ali *et al.* [58] proposed the diagonal and vertical routing protocol (DVRP) for underwater wireless sensor networks in order to reduce the network load and improve throughput by calculating a flooding zone. The purpose of this flooding zone is to prevent flooding the whole network, thereby increasing the reliability of the network. The authors demonstrated improvement over DBR in simulated results.

All of these existing routing protocols for underwater sensor networks do not consider spectrum scarcity issues caused by limited communication frequencies. To meet the increasing demands of underwater acoustic users, it is essential to propose a cognitive routing protocol that takes the spectrum scarcity issue into account. Luo *et al.* [59] proposed

a receiver-initiated spectrum management system for UCANs. They allowed acoustic users to utilize the spectrum with both 'natural acoustic systems' and 'artificial acoustic systems' efficiently and courteously. They increased the overall data transmission rate by combining a collision avoidance mechanism with joint power and channel allocation. Their results showed better performance for both the tree topology and the partially connected mesh topology by integrating spectrum sensing on the physical layer with spectrum sharing on the medium access control layer.

Therefore, due to harsh underwater environments, implementing a routing protocol under water is a challenging task, especially when utilizing the idle spectrum while keeping PU activity undisturbed. Moreover, the sound signal in underwater acoustic channels is attenuated by multipath interference or fading, developing an acoustic system that is truly wideband [60]. To overcome these drawbacks of underwater acoustic channels, multicarrier modulation seems to be a solution. Orthogonal frequency division multiplexing (OFDM) has been widely studied as a popular method for both terrestrial and underwater communications in order to decrease inter-symbol interference and overcome the long delay spread. Hence, a novel cognitive routing protocol based on an OFDM modulation scheme is an essential requirement for underwater networks. However, in order to maintain a stable link to reach the destination while avoiding interference with diverse acoustic systems and keeping the activity of licensed users undisturbed and cope with the shortcomings of long propagation delay, selection of a relay node is one of the key design factors in underwater sensor networks. Consequently, selecting a relay node that incurs minimum transmission delay to send packets to the destination improves the overall network performance. In view of that, forming an underwater cognitive sensor network that guarantees scalability and sustainability while co-existing with multiple acoustic systems is a primary aim of this chapter.

To the best of our knowledge, combining cognitive principles with routing schemes for underwater sensor networks has not yet been considered. OFDM-based spectrum-aware routing (OSAR) is the first work implementing a cognitive routing protocol in UCANs that simultaneously considers spectrum sensing and routing for underwater sensor networks. OSAR performs spectrum sensing to evaluate the surrounding environment, and then finds the best relay node to deliver packets to the destination. Spectrum sensing is performed with an OFDM-based energy detection scheme. The querying node first finds a common idle channel by comparing its local sensing results with all the neighbors within the transmission range, and then selects a relay node for the next hop that has the minimum transmission delay. Two sensor nodes can only communicate while protecting the activity of both 'natural acoustic users' and 'artificial acoustic users' if they find a common free channel. Therefore, the goal of this chapter is to provide a stable route for communications between sensor nodes and surface buoys in underwater environments by jointly selecting channel and relay.

The rest of this chapter is organized as follows. We introduce the framework of OSAR in Section 4.2, with a detailed description of channel- and relay-selection mechanisms. Section 4.3 demonstrates the simulation results of the proposed solution. Finally, Section 4.5 concludes this chapter and points out some future directions for this work.

4.2 Proposed scheme

In this chapter, the OSAR protocol for underwater cognitive acoustic networks is proposed. The objective of this proposed scheme is to ensure cognitive routing in underwater sensor networks by considering both natural acoustic systems and artificial acoustic systems as primary users. We consider an underwater cognitive sensor network with N sensor nodes and L primary users. The purpose of using cognitive principles in underwater sensor net-

works is to increase the spectrum opportunities for different users communicating with each other in the ocean. OSAR is a spectrum aware routing scheme in which each node first senses its surrounding environment to make sure that the channel is free from both natural acoustic systems and artificial acoustic systems, and then choose the best relay node as the next forwarder to reach the destination. The two CA nodes can only communicate with each other when they have consensus on a common idle channel. The goal of this scheme is to minimize the transmission delay by selecting the best relay nodes between the source and destination. Likewise [53], we consider one-dimensional (1D) geographic routing in a single upward direction to sea level.

Sensor nodes are assumed to be equipped with acoustic modems and depth sensors in order to configure their depths and measure the distance to the surface of the ocean. All nodes periodically update the depths of their neighboring nodes. This helps the querying node to find the best relay node that incurs the minimum transmission delay. We divide the acoustic spectrum into M channels. CA users perform spectrum sensing to find an acoustic spectrum not utilized by the PUs. Spectrum sensing is a challenging problem in underwater networks because both types of primary users in the underwater environment are mobile, and we cannot predict the position of natural acoustic systems. Moreover, another critical issue in underwater acoustic networks is time delay. For that reason, we use an energy detection scheme to detect the presence of a PU, because it is the simplest technique that has a short sensing time, and it is useful when little or no information about PU signals is available. One distinguishing issue with an acoustic signal is that it is attenuated by fading or multipath interference due to sound absorption and rough sea surfaces. To overcome fading or multipath interference, we use OFDM as a modulation technique. OFDM simultaneously uses multiple sub-bands to transmit the packets between two communicating sensor nodes. As this is a cognitive routing scheme, cognitive users need

to sense the spectrum continuously to find a number of free subcarriers for communications among different users. This means that a link between two communicating acoustic nodes has a set of sub-channels/subcarriers free from PU activity. Therefore, to improve the data rate, a packet can be transmitted over a number of free subcarriers. Accordingly, we assume that the primary signal is an acoustic OFDM signal. Before going into a more in-depth description of OSAR, we first discuss how sound signals from marine mammals can be detected and how the spectrum can be utilized in the presence of marine mammals.

***Discussion*:** One might think about how a sound signal from marine mammals is detected by the CA users. Here, we briefly discuss the assumptions we make for sound signals produced by marine mammals. Marine bioacoustics [61] is used by researchers and marine scientists to record the sounds produced by marine animals in order to study their behavior and relationships with the marine environment. Various studies have been carried out to measure and detect different sound patterns produced by different marine mammals [62, 63]. Researchers have placed various hydrophones on the sea floor to detect the sound signals. Like these studies, we assume that the patterns of sound signals are known and each CA user can detect this signal frequency by using an energy detector. The methods marine scientists used to measure animal sounds are not part of this work. Our motive is to protect the signal produced by either marine mammals or SONAR systems from interfering with CA users. We will further explore this problem in the near future. Additionally, the sound patterns of marine animals like whales, dolphins, etc., have pauses of a few seconds, and multipath arrivals of sound with echoes are considered noise. Moreover, mammals can hear each other at up to six miles apart [63]; beyond that distance, the sound signal is also considered noise. Therefore, the spectrum can be utilized even when marine mammals are communicating with each other, either during pauses or when CA users are far enough from legitimate users to keep PUs safe. For that reason, we model PU activity as

an exponential on/off activity pattern. In SONAR systems as a PU, we assume that both transmitters and receivers are equipped with transducers. However, for natural acoustic systems, receivers only are equipped with transducers.

4.2.1 Spectrum sensing and the channel model

In this subsection, we perform spectrum sensing to detect the presence of a PU signal on an underwater acoustic channel. The significant aspect of the underwater acoustic channel is the dependence between bandwidth and frequency and the distance between the communicating sensor nodes [64]. Spectrum sensing is done with an energy detection scheme. We consider an OFDM-based cognitive acoustic system in which the PU-OFDM system consists of P subcarriers. The CA system performs sensing operations to detect which subcarriers are free from PU activity.

In an OFDM modulation scheme [65–67], the symbols of the PU first pass through a serial-to-parallel converter to generate parallel streams, and they then enter the P-point inverse fast Fourier transform block, which generates transmit samples. Then, multiplexing is done to generate serial streams of PU symbols, after which a cyclic prefix is added to the original samples. Finally, the OFDM-based PU samples are transmitted through an underwater acoustic channel. On the receiver side, CA users receive samples from the acoustic channel, remove the cyclic prefix, and allow these samples to pass through a serial-to-parallel converter to enter the P-point FFT block. The receiver detects the total number of subcarriers that can be used by CA users for communicating with each other. Hence, the received signal after the FFT operation is defined as:

$$y_{q,i}(n) = s_{q,i}(n) + w_{q,i}(n), \tag{4.1}$$

where $q = 1, ..., P-1$ is the subcarrier index.The received signal is then modeled as a binary hypothesis test in order to detect the presence or absence of a PU signal on the underwater

acoustic channel. The two hypotheses are defined as follows:

$$y_{q,i}(n) = \begin{cases} w_{q,i}(n), & H_0 \\ s_{q,i}(n) + w_{q,i}(n), & H_1 \end{cases} \tag{4.2}$$

where $i = 1, ..., N$, $s_{q,i}(n)$ is a complex PU signal at subcarrier q, and $w_q, i(n)$ is noise. The energy-based test statistic in discrete domain is given as follows:

$$y_{E_{q,i}} = \sum_{n=1}^{W} y_{q,i}[n]\tilde{y}_{q,i}[n] \tag{4.3}$$

where W is the time-bandwidth product, and $\tilde{y}_{q,i}[n]$ is the conjugate signal of $y_{q,i}[n]$. The key parameter in the underwater realm is the acoustic propagation speed, which is assumed to be 1500 m/s in most of the literature. However, the propagation speed in acoustic theory is mainly affected by depth, temperature, and salinity, and can be modeled in meters per second as follows [54]:

$$q(z, s, T) = 1449.05 + 45.7T - 5.21T^2 + 0.23T^3 + (1.333 - 0.126T + 0.009T^2)(s - 35) \\ +16.3z + 0.18z^2 \tag{4.4}$$

where z is the depth in kilometers, s is the salinity in parts per trillion, and $T =$ (temperature in $^\circ C$)/10.

Another peculiar property of an underwater acoustic channel is the dependence of path loss $A(d, f)$ on the signal frequency, f. This path loss while traveling over distance d affects the received signal power, which in turn changes the signal-to-noise-ratio (SNR) for each user transmitting at f. Therefore, each sensor node experiences a different SNR, which is calculated as follows [64, 68]:

$$SNR(d, f) = \frac{P_T}{A(d, f)N(f)\triangle f} \tag{4.5}$$

where P_T is the transmitted power, $\triangle f$ is the width of frequencies, and $N(f)$ is the noise power spectral density, which is calculated as:

$$N(f) = N_t(f) + N_s(f) + N_w(f) + N_{th}(f) \tag{4.6}$$

The right-hand side of (4.6) refers to the superposition of four components: turbulence (t), shipping and other human activities (s), wind and waves (w), and thermal noise (th). These four components are calculated as follows [69]:

$$\begin{aligned} N_t(f) &= 17 - 30log_{10}(f) \\ N_s(f) &= 40 + 20(s - 0.5) + 26log_{10}(f) - 60log_{10}(f + 0.03) \\ N_w(f) &= 50 + 7.5\sqrt{w} + 20log_{10}(f) - 40log_{10}(f + 0.4) \\ N_{th}(f) &= -15 + 20log_{10}(f) \end{aligned} \tag{4.7}$$

$A(d, f)$ in (4.5) is defined as $A(d, f) = d^k a(f)^d$, where k is the path loss exponent that models the geometry (spherical and cylindrical) of propagation, and $a(f)$ is the absorption coefficient, which can be obtained by Thorp′s formula [70]:

$$A(f) = \frac{0.11f^2}{1 + f^2} + \frac{44f^2}{4100 + f^2} + 2.75 \times 10^{-4} f^2 + 0.003 \tag{4.8}$$

where $A(f) = 10log_{10}a(f)$.

Acoustic communications in underwater systems present various challenges due to environmental conditions that are primarily related to accurate modeling of the channel behavior [71]. To propose an appropriate algorithm for underwater cognitive routing networks on both the physical link layer and the network layer, an introductory requirement is to design a relatively accurate channel model. Guerra *et al.* [72] showed the significant difference in using a ray tracing tool over empirical propagation formulas. The empirical equations cannot model complex phenomena, such as sound speed profile, bathymetry, and

sound propagation in bottom sediments, whereas a Bellhop ray tracing tool provides an accurate emulation of sound propagation and a relatively accurate channel model. However, the authors also claimed that accuracy provided by a Bellhop simulator is only limited to channel attenuation. For modeling noise in an underwater channel environment, empirical equations are still used in simulations. Also, Qarabaqi and Stojanovic [73] claimed that ray theory seems to be a viable solution for providing an accurate picture of an underwater acoustic channel. We second them, therefore, like Toso *et al.* [74] and Bahrami *et al.* [75], and in this study, we use beam tracing tools, such as the Bellhop [76], to compute the channel attenuation to take into account ineluctable channel variations.

In this proposed scheme, each sensor node first senses the spectrum individually by using (4.2), and then exchanges its local sensing results with all the nodes within the acoustic transmission range to find the next forwarder in its vicinity. The querying node then selects the forwarder with a shallower depth if and only if they both have consensus about the common idle channel and they both meet the other constraints (explained in the next subsection) to establish a routing path to the surface. The following section explains how routing is done in underwater communications systems using the channel state.

4.2.2 Relay selection

To select the best relay node in order to make a stable route between the source and destination, we propose an efficient routing scheme by using the sensing results obtained as described in the previous subsection. To initiate routing, the source node first broadcasts a beacon message to all its neighboring nodes. The beacon packet includes the sender′s ID, depth, channel state, and speed. The channel state and speed are calculated from (4.2) and (4.4), respectively. The channel state is defined as the state that represents either the channel under observation is idle or busy. Each sensor node updates its table by receiving

the beacon messages from neighboring nodes. Each node compares its depth with the source/querying node. The nodes at the same and greater depth to the querying node will drop the packet (i.e. they will not participate in the routing protocol). The nodes making a positive advance toward the destination will be added to P_i^D. The nodes in P_i^D compare their local sensing results, and if they find a common idle channel between two of them (i.e. querying node and relay node), they will be added to N_i (the neighbor set of node i with common idle channels). It is noteworthy that two sensor nodes can only communicate with each other in order to form a path between the source and destination if they have consensus about a common idle channel. The selected relay nodes now jointly calculate the packet size, capacity, propagation delay, and estimated number of hops to the destination. These parameters are jointly calculated as transmission delay, which is defined as

$$TD_{ij}^{ch} = \left(\frac{L_P}{r_{ij}^{ch}} + PD_{ij}\right)\widehat{N}_{ij}^{Hop} \tag{4.9}$$

where ch is one of the M channels; L_P is the packet size; r_{ij}^{ch} is the data rate of link (i, j), defined as $r_{ij}^{ch} = C_{ij}^{ch} = \int_{f_l^{ch}}^{f_h^{ch}} log_2(1 + \frac{S(f)}{N(f)})df$, where C_{ij}^{ch} is the capacity of the common idle channel between the two communicating nodes is as assumed elsewhere [64,77], f_h and f_l are upper and lower frequencies of each channel, respectively, and $S(f)$ is the power spectral density of the transmitted signal. If there is more than one common channel between two communicating nodes, then the querying node randomly selects a channel. PD_{ij} is the propagation delay, defined as $PD_{ij} = \frac{D_{ij}}{q(z,s,T)}$; $D_{ij} = Depth_i - Depth_j$; $\widehat{N}_{ij}^{Hop} = max\left(\frac{D_{iD}}{<D_{ij}>_{iD}}, 1\right)$, in which D is the destination node, and $< D_{ij} >_{iD}$ is the projection of distance D_{ij} on the line connecting source to destination.

This algorithm allows each node to select its best next hop with the objective of minimizing the transmission delay while taking the condition of the common idle channel between the two communicating nodes into account. The key idea behind OSAR is similar

to greedy routing, which is to select a node that is farthest from the source node (closest to the destination). However, the selection of the next hop node by considering only the propagation delay seems like an unjustifiable issue in underwater cognitive acoustic networks. This is because the acoustic speed is very small in comparison with the speed of light used in terrestrial communications and finding a common idle channel is an elementary step for sensor nodes to communicate. Therefore, in this scheme, we modify the greedy routing algorithm by considering transmission delay. Our algorithm selects the farthest node based on (4.9), which not only considers the estimated number of hops but also considers the propagation delay along with the data rate and packet size. The selection is defined in terms of an optimization problem, as follows:

$$\begin{aligned} \textbf{Find:} \qquad & j = arg \min_{j \in N_i \subset P_i^D} TD_{ij}^{ch} \\ \textbf{Minimize} \qquad & TD_{ij}^{ch} = \left(\frac{L_P}{r_{ij}^{ch}} + PD_{ij} \right) \widehat{N}_{ij}^{Hop} \end{aligned} \tag{4.10}$$

where N_i is the set of nodes within i's transmission range that has a common idle channel with node i and P_i^D is the set of nodes making positive advance towards D.

To summarize the whole idea, let us assume some sensor nodes are distributed in the target area, as shown in Fig. 4.1. The destination in this study is any surface buoy located at the sea level. Basically, the original destination is the monitoring center on land, but this final route from the sensor node (source) in the ocean to a monitoring center on land will be our future work by jointly handling wireless and acoustic communications. Here, we assume that all the surface buoys are at the same depth, and each sensor node in the network recorded the depths of the surface buoys. We assume marine mammals are one kind of PU in this study. When a source node, as shown in Fig. 4.1, wants to communicate with a surface buoy, it starts looking for the best relay node for establishing a stable path from itself to the surface of the ocean. The very first task of the querying node is to find

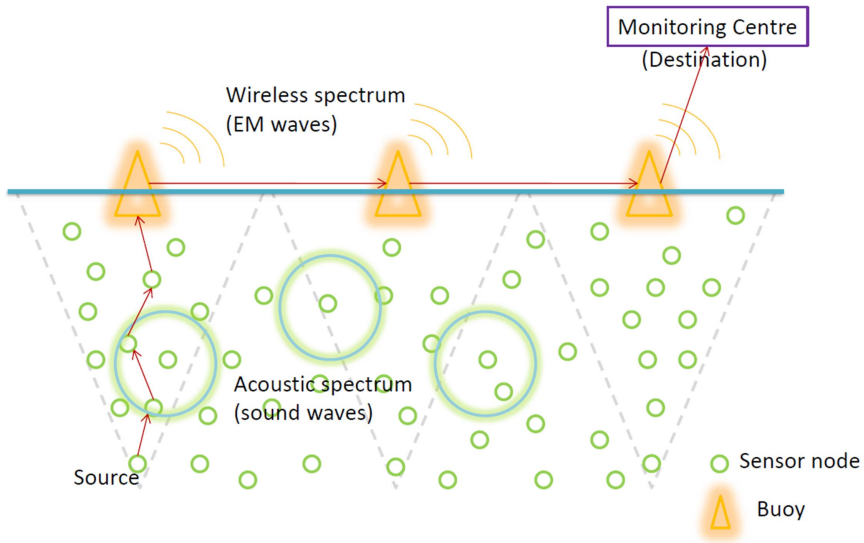


Figure 4.1: Underwater cognitive acoustic network.

a common idle channel. Therefore, each sensor node first performs spectrum sensing to detect the number of subcarriers free from PU activity. The sensor nodes then exchange their local sensing results with the neighboring set of all nodes present in P_i^D. The nodes having common idle channels form another set: N_i. From this set, the querying node selects the node that has the minimum transmission delay among those relay nodes that have an idle channel in common with the querying node. Thus, the process is repeated by each relay sensor node until the packet reaches the destination. The flowchart for selection of the next hop node in OSAR is represented by Fig. 4.2.

4.3 Simulation results and discussion

OSAR is simulated in ns-MIRACLE [78] connected to a Bellhop channel simulator [76] via the World Ocean Simulation System (WOSS) [72] interface. WOSS is basically a powerful

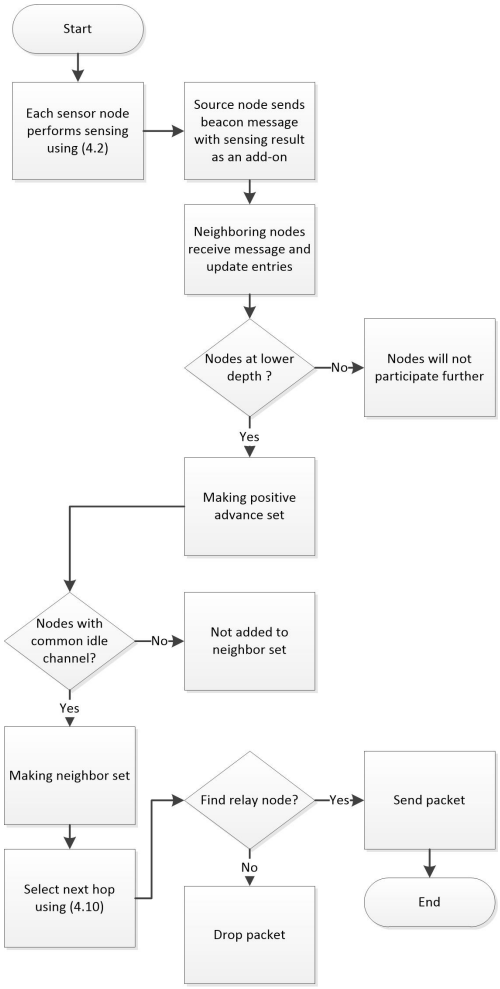


Figure 4.2: Flowchart representing OSAR protocol.

tool that provides a connection between ns-MIRACLE and the Bellhop channel simulator. It takes the scenario information (geographic location of all the sensor nodes) from the network simulator and provides the environmental data queried from the oceanographic databases to the channel simulator. As mentioned before, the Bellhop channel simulator uses ray theory to model relatively accurate channel characteristics by employing the information about the sound speed profile, bathymetry, and types of bottom sediments. After some post-processing [71], WOSS finally returns the channel attenuation and interference to the

ns-MIRACLE network simulator.

In our scheme, randomly placed sensor nodes are distributed in a target area of 500 m × 500 m × 500 m, each having a transmission range of 250 m. Packet size L_P is assumed to be fixed (i.e. 64 bytes). The number of CA users, N, varies between 10 and 30, and the acoustic spectrum band (10-40 kHz) is divided into M= 5 channels. Each channel can be occupied by a licensed PU. The bandwidth of each channel is 6 kHz with carrier frequencies of {13,19, 25, 31, 37} kHz. This means that a band of frequencies is free for use by legitimate users in order to transmit data packets over a number of free subcarriers. The total number of subcarriers, $P = 128$, each have carrier spacing of 46.875 Hz. As we know that channel sensing is affected by sensing time in any cognitive radio network, we therefore use fewer subcarriers to make it reasonable for underwater cognitive acoustic networks. For the same reason, we use the length of cyclic prefix, $T_{CP} = 12.4$ ms with symbol duration, T_s = 21.33 ms which is greater than the typical value of delay spread in underwater networks, i.e. approximately 11 ms [68]. The PU is $L = 1$ in this study, and it can move up to a distance of 1000 m from the target area of CA users, because marine mammals can listen to each other at up to six miles apart [63]. Beyond this distance, their signals are considered noise. The PU is moving randomly in the network. The transmission power, P_T=150 dB re μ Pa, which is within the range of the power value for acoustic signals of dolphins [62].

We evaluated DBR [52] and DVRP [58], each in combination with an energy detector-based spectrum sensing scheme [79] for underwater cognitive sensor networks just for reference. For simplicity, we denote these schemes as Cog-DBR and Cog-DVRP, respectively. DBR is a depth-based routing protocol proposed for underwater sensor networks that selects its next forwarder in a single upward direction. Cog-DBR modifies the DBR protocol such that each sensor node first senses the spectrum. Then each node exchanges its local sensing results with all the sensor nodes in its neighborhood to select a common idle

channel from among the set of forwarding neighbors. Finally, it implements the key idea of DBR to choose the final appropriate relay node. Another modification in DBR is that if the source/relay nodes do not find the next hop with a common channel at the maximum distance, Cog-DBR selects one at a greater depth within the transmission range. DVRP is a flood-based routing protocol for underwater sensor networks that forwards data packets (based on the flooding zone angle) from the sender nodes towards the surface of the ocean. It selects the next-hop node within the defined flooding zone. Like Cog-DBR, Cog-DVRP modifies the DVRP protocol, such that each sensor node exchanges the spectrum sensing results within its defined zone in order to find a common idle channel. The two communicating nodes, having consensus about a common idle channel, then exchange data packets to make a stable route between source and destination.

Fig. 4.3 shows the performance of average delay as a function of the number of sensor nodes with the number of channels as a parameter. Average delay is defined as the average time required by a packet sent from the source node to reach the surface buoy. The average delay decreases with an increase in the number of sensor nodes. The reason for the decrease is the greater connectivity in the network due to the increase in the number of sensor nodes. With fewer sensor nodes, the packet usually has to wait longer than normal. However, in addition to this reason, finding a common idle channel in cognitive communication scenarios is another cause of packet delay. As our goal is to minimize the transmission delay, we therefore select the next relay node that needs a relatively minimum time to deliver the packet to the next hop. Also, this relay selection continues until the packet reaches any buoy at the surface of the ocean. On the other hand, Cog-DBR makes the next-hop decision based on greedy routing after finding a common idle channel between two communicating nodes. Hence, OSAR outperforms Cog-DBR because it selects the next relay node based on transmission delay in order to make a stable path between the source

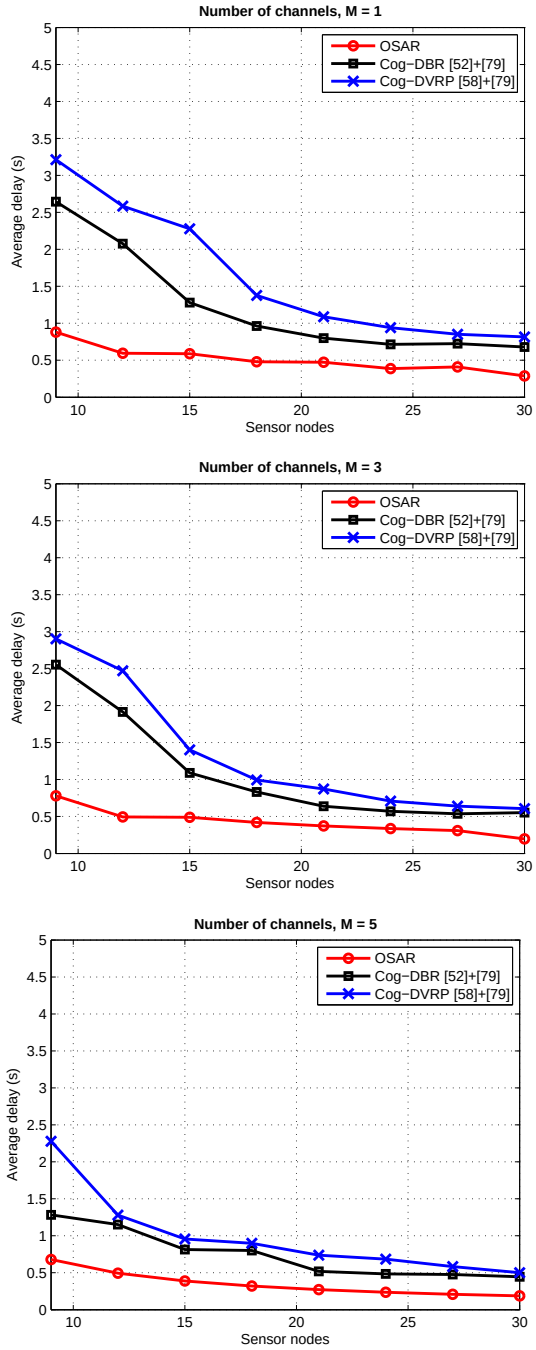


Figure 4.3: Performance comparison between OSAR, Cog-DBR, and Cog-DVRP for average delay as a function of the number of sensor nodes with different numbers of channels, M: (a) Average delay when $M = 1$, (b) Average delay when $M = 3$, and (c) Average delay when $M = 5$.

and destination. Also, both OSAR and Cog-DBR outperformed Cog-DVRP. It can be seen from Fig. 4.3 that the delay for Cog-DVRP is even higher than Cog-DBR. This is because Cog-DVRP restricts the neighboring set for the querying node. The querying node is bound to select a relay node within the flooding zone. As this is a cognitive routing scheme, the elementary step of selecting a common idle channel between two communicating nodes further degrades the performance of this reference scheme. As a result, finding a relay node within a flooding zone decreases network performance by reducing the number of sensor nodes. Fig. 4.3 also shows that increasing the number of channels increases the chance for the sensor nodes to have even more common idle subcarriers. When there is only a single channel in the network, the number of idle subcarriers is also fewer; hence, the CA users face difficulty in accessing subcarriers free from a PU. Increasing the number of channels allows CA users to opportunistically access the common idle sub-bands, and increases the chances for more sensor nodes to participate in the network. In this regard, the average delay under OSAR is the lowest compared with other scenarios when the number of channels is $M = 5$, as shown in Fig. 4.3c.

Fig. 4.4 shows the packet delivery ratio of OSAR, Cog-DBR, and Cog-DVRP. Packet delivery ratio is defined as the ratio of the number of packets delivered to any surface buoy to the number of packets generated by the source node. The delivery ratio increases with an increase in the number of sensor nodes. We achieve 93% packet delivery under OSAR when there are more sensor nodes in the network, compared with both of the other reference schemes. The reason is the difference in the selection of the relay node. When the selection is based on the DBR protocol, the querying node may select a relay node that does not make a stable link due to greater delay, resulting in link failures and a low packet delivery ratio. In a cognitive underwater environment, in addition to underwater environmental challenges, another factor that affects the packet delivery ratio

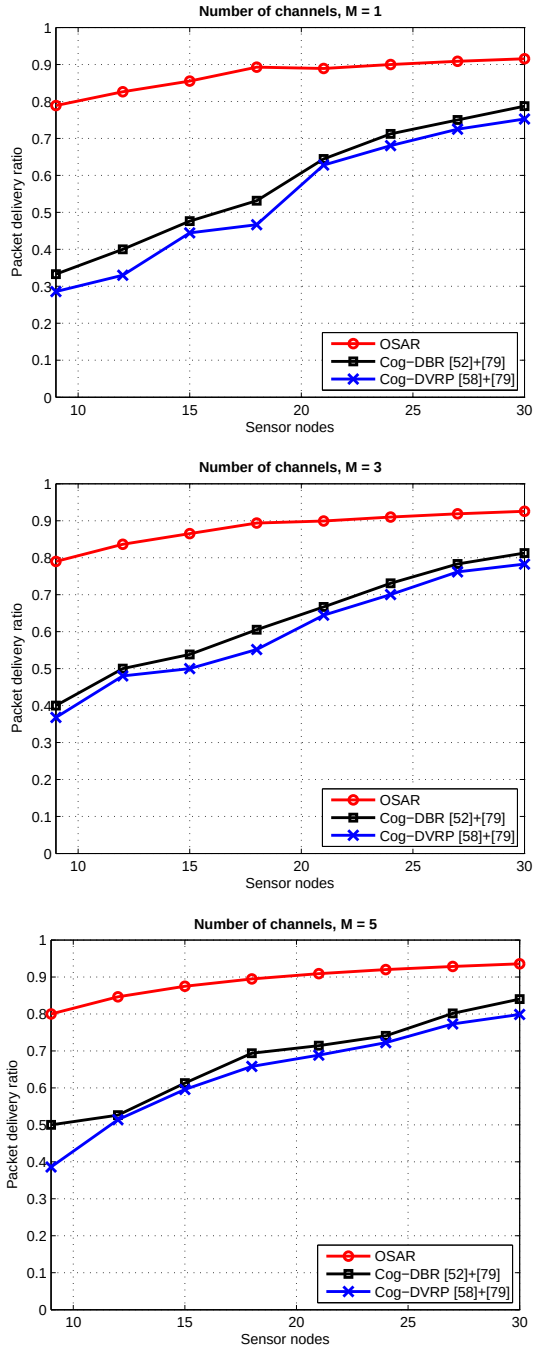


Figure 4.4: Performance comparison between OSAR, Cog-DBR, and Cog-DVRP for a packet delivery ratio as a function of the number of sensor nodes with different numbers of channels, M: (a) Packet delivery ratio when $M = 1$, (b) Packet delivery ratio when $M = 3$, and (c) Packet delivery ratio when $M = 5$.

is the selection of a common idle channel. However, when OSAR is the cognitive routing scheme, the packet delivery ratio is higher for different numbers of channels, in comparison with the other two reference schemes. The reason is the selection of the relay node based on minimum transmission delay. OSAR only selects a node that delivers the packet quickly, hence, reducing delay and increasing the packet delivery ratio. Furthermore, we achieve almost the same packet delivery ratio from OSAR with varying numbers of channels. This is because OSAR selects a relay node from the set of nodes with an idle channel in common with the querying node. Once the querying node finds a relay node with minimum delay, it will deliver the packet to its next relay node. The relay selection continues in this pattern until the packet finally reaches the destination. It is the value of (4.9) that changes at every next selection of a relay node, making changes in the average delay. For that reason, the number of packets delivered to the destination for different numbers of channels in OSAR is almost the same; hence, the delivery ratio is almost the same. Fig. 4.4 also shows that the performance of Cog-DVRP is poorer than the other two schemes. This is because the selection of relay nodes in Cog-DVRP is restricted by the flooding zone, and therefore, its delivery ratio is lower than the other two schemes. Like Cog-DBR, Cog-DVRP also makes the next-hop decision based on the distance from the querying node. Hence, this cognitive routing scheme, finding a common idle channel within the flooding zone, reduces the chances of successful delivery of packets. Therefore, OSAR outperforms both Cog-DBR and Cog-DVRP.

Fig. 4.5 shows the overhead ratio of OSAR, Cog-DBR, and Cog-DVRP as a function of the number of sensor nodes, with the number of channels as a parameter. The routing overhead for both the proposed and reference schemes increases with an increasing number of sensor nodes in the network. We observed a similarity in all the schemes in terms of an increase in the overhead ratio when the number of sensor nodes increases and the number

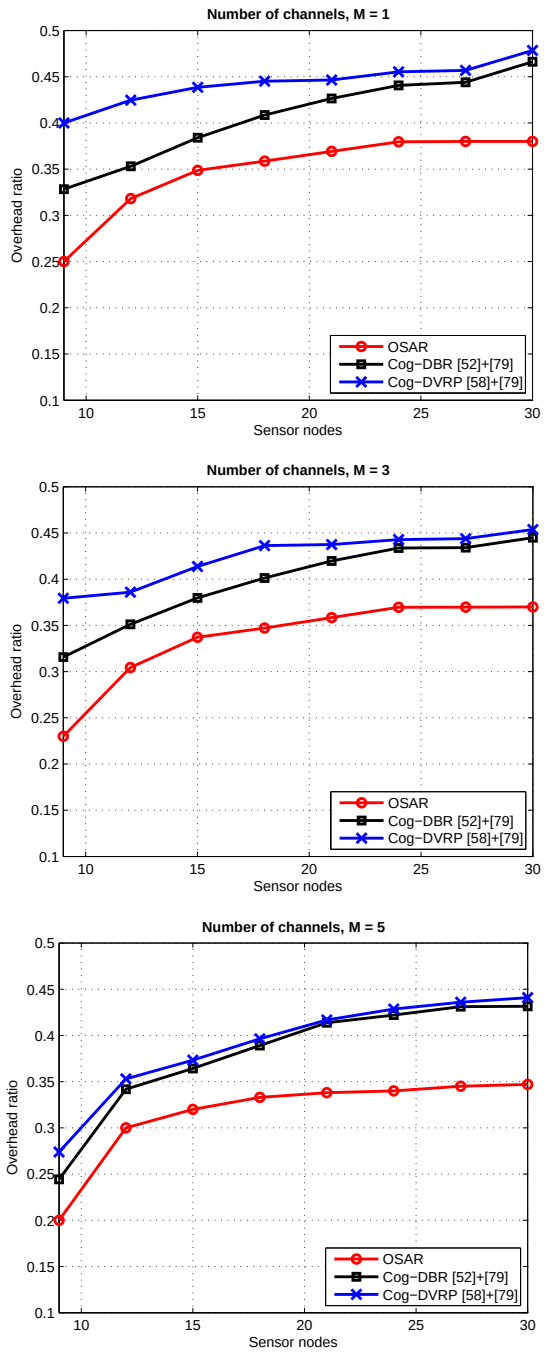


Figure 4.5: Performance comparison between OSAR, Cog-DBR, and Cog-DVRP for the overhead ratio as a function of the number of sensor nodes with different numbers of channels, M: (a) Overhead ratio when $M = 1$, (b) Overhead ratio when $M = 3$, and (c) Overhead ratio when $M = 5$.

of channels decreases. The more sensor nodes, the higher the message update rate. However, OSAR outperforms both reference schemes. The reason for the better performance is our selection criterion that reduces unnecessary control messages by picking the next-hop node based on transmission delay, and by not restricting the size of the neighboring set. The overhead ratio for both Cog-DBR and Cog-DVRP is higher than OSAR. In both these schemes, the querying node may select a relay node that does not make a stable path due to greater delay; hence, resulting in link failure that incurs large overhead. Also, calculating the flooding zone further reduces the chances of successful delivery of packets. This is because sensor nodes may not find a common idle channel for communication, which therefore increases the overhead ratio. It can be seen in Fig. 4.5 that the maximum overhead ratio of our proposed scheme is almost 38%, whereas for the reference schemes, it is more than 45%. Fig. 4.5 also shows that for fewer channels, M, the subcarriers are mostly occupied by a PU. Increasing the number of channels increases the free subcarriers in the network, and thereby decreases overhead by providing a large number of unused subcarriers to the sensor nodes for stable communications. In this regard, it decreases the overhead of control messages used to find an idle channel. A complete analysis of the simulated results in this chapter shows that for an underwater cognitive routing scheme, the selection of a relay node based on transmission delay makes the network more stable than distance-based schemes. Another observation from these results is that a restriction of the selection zone is not suitable for underwater cognitive routing schemes, as this result in poor network performance. This is because nodes must reach consensus about a common idle channel between the two communicating sensor nodes. Also, we determined that using an OFDM-based energy detection scheme in this band-limited cognitive underwater environment increases the chances of finding more idle subcarriers for sensor nodes. In so doing, it provides multiple sub-bands simultaneously to transmit the packets between two communicating sensor nodes.

4.4 Chapter summary

This chapter proposed a novel routing scheme for underwater cognitive sensor networks. The combination of both channel selection and relay selection in underwater communication systems makes this method unique. Both natural acoustic systems and artificial acoustic systems are considered PUs in this scheme. When a source node located somewhere in the deep ocean wants to send data packets to any surface buoy located at the sea level, it selects the best relay to make a stable path between itself and the destination. A set of neighboring nodes having consensus about a common idle channel is formed after exchanging local sensing results. Then, a node that has the minimum transmission delay is selected as the next relay node. An OFDM-based energy detection scheme is used for spectrum sensing. The results in this chapter show better performance for average delay, packet delivery ratio, and overhead ratio. This work is valid only for underwater acoustic communications. In the future, we will extend this work to hybrid communications to reach a monitoring center on land.

Chapter 5

Software-Defined Cognitive Vehicular Networks

5.1 Introduction

Software-defined networking (SDN) is an emerging technology that increases network intelligence by separating the control plane from the data plane [80]. This separation provides efficiency, flexibility, management, and vendor independence (due to a standardized interface). SDN technology brings intelligent management by shifting from hardware-dependent to software-defined architectures. It simplifies networking in the context of development and deployment of new protocols [81, 82]. In conventional networks, each switch or router is individually bound to perform all functions (routing, forwarding, and network management), which causes inefficient utilization of resources, network inflexibility, and improper time management. However, SDN enhances network compatibility by reducing forwarding delay as this new paradigm eliminates the need for hop-by-hop flooding at each intermediate node while discovering a route [83, 84].

SDN decoupling also enables a directly programmable forwarding plane where different nodes in the network act as forwarding devices only; thereby, all the functionalities are now centrally controlled. The control plane supplies flow rules to the data plane about packet forwarding. The layer above the control plane (i.e. application layer) allows users to change their behavior for each requirement accordingly [83, 85–87]. A centralized controller is in high demand nowadays due to the massive amounts of nodes and data in each network. It is responsible for deploying new protocols along with programmatic management of the whole network and dynamic allocation of the network resources [81, 86]. Due to this intelligent centralized controller, network operators can now easily program, modify, and configure these protocols without the need to do this individually on each network device. This means that the network can be intelligently controlled in a vendor-independent manner these days, since devices may come from multiple vendors. The SDN controller introduces high-priority rules for packet forwarding, thereby generating advanced routing configurations. As a result, the switches or routers just accept the policies sent by the controller, and follow the instructions of the controller per-flow rules to forward the packets in the network without having, determining, and/or implementing various protocols′ standards, thereby making the whole network directly controlled, managed, and programmed by the controller [82]. In view of the network resources, SDN also eases spectrum assignment in an efficient manner due to its logical centralized controller [87–89].

A standard protocol is required to communicate between the data plane and the control plane. OpenFlow is one of the well-known and standardized protocols in [90]. The key benefit of OpenFlow is that the existing hardware can be efficiently utilized under SDN [85]. These days, many new routers are equipped with an interface for OpenFlow. They can support hybrid functions for both SDN and conventional communications [89]. OpenFlow-enabled network devices contain three entries in each flow table; rules, actions,

and counters. Rules are the policies, actions are the commands that describe how packets should be forwarded, and counters are the statistics that count the number of packets and bytes for each flow. A *secure channel* is used between network devices and the controller for the exchange of flow tables and data packets [82]. Two types of messages are used between the control plane and the data plane: *packet-in* and *flow Mod*. *Packet-in* messages are used to ask the controller for flow modification if any SDN switch does not know how to handle the packet. A *Flow Mod* message is sent by the controller to data plane switches/nodes [91].

Existing networks on land, the sea surface and in the ocean need a new candidate to improve network performance and communications reliability. Due to the above-mentioned services provided by SDN, many researchers found it a suitable candidate for different types of network systems (including VANETs, maritime networks, and UANs), in order to overcome the limitations in these networks [88, 92–96]. Moreover, due to decoupling, the controller can adaptively deploy routing protocols in highly dynamic and challenging environments, which brings an efficient utilization of existing routing protocols in VANETs, maritime networks, and UANs. In the next chapters, we apply SDN technology in CR-VANETs, cognitive maritime networks, and UCANs, respectively to overcome the shortcomings with the existing architectures in these domains. In that order, this chapter proposes a novel cognitive routing protocol for software-defined vehicular networks to find a stable route between source and destination.

To the best of our knowledge, combining cognitive principles with routing schemes in VANETs by using the SDN concept has not been considered so far. The closest studies are a few implementations in cognitive radio networks [97] to deal with spectrum shortage issues, and in VANETs [83, 88] to recover connection failures, to enable fast network invention, and to propose routing protocols. Very few protocols have been proposed for routing in software-defined vehicular networks (SDVNs). These SDN-based routing protocols are

basically an amendment to existing routing protocols for MANETs and VANETs. Sudheera *et al.* [91] proposed a novel SDVN architecture that satisfies the delay constraints in VANETs. Liu *et al.* [98] proposed a geographic SDN-based routing scheme for VANETs to enable efficient transmission and to deliver periodic warning messages to the geographic area of the destination. SDN-based vehicle ad-hoc on-demand (SVAO) routing protocol [99] separates the control layer and the data forwarding layer to enhance data transmission efficiency in VANETs. Hierarchical software-defined vehicular (HSDV) network [100] is another protocol proposed to improve network stability with a central SDN controller. A SDN-based geographic routing (SDGR) protocol [101] computes optimal routing paths between source and destination. Zhu *et al.* [102] proposed a SDN-based routing framework for efficient propagation of messages in VANETs by selecting the global optimal route from the source to the destination. A distributed software-defined infrastructure-less vehicular network (dSDiVN) [103] was proposed to ensure a reasonable end-to-end delay and to support delay-sensitive services. The authors claimed that it is the first work that integrates SDN in infrastructure-less VANET environments.

None of the routing protocols described above consider spectrum scarcity issues caused by the inadequacy of DSRC channels. A routing scheme considering both spectrum and routing issues together was proposed by Kim *et al.* [28]. CoRoute is one of the routing protocols in the area of CR-VANETs for city scenarios that makes the best use of available Wi-Fi bandwidth by causing fewer disruptions to residential users.The Cognitive Routing Engine (CRE) was proposed by Francois and Gelenbe [104] to find near-optimal paths for the current state of the network. CRE was proposed to combine cognitive capabilities with routing by using an SDN approach. But this protocol was not proposed for CR-VANETs. Consequently, combining cognitive principles with routing schemes to design an algorithm for a CR-SDVN has not yet been considered. The study in this chapter is the first work

implementing a cognitive routing protocol in SDVN that simultaneously considers spectrum sensing and routing for both V2V and V2I communications.

The main objective of this chapter is to combine a cognitive capability with a routing technique in vehicular networks by using the SDN approach.The chapter intends to overcome the problems of spectrum scarcity, intermittently connected networks, high latency, and the large overhead in CR-VANETs by implementing a novel cognitive routing protocol for cognitive radio software-defined vehicular networks (CR-SDVNs). The goal here is to select the best route between source and destination that maximizes the path duration among all the paths. Likewise chapter 2, spectrum sensing is done by a BP algorithm [31] in which each node makes a final decision about the availability of channels by iteratively combining the beliefs of all neighboring nodes. The SDN controllers programmatically configure the traffic and have a global view of the network. This proposed scheme has a single main controller (MC) and several local controllers (LCs). LCs are fixed RSUs that have a localized global view of the network. Vehicles send requests to LCs, querying for a route to the target node. The LC quickly responds to the request if it has a route to the destination; otherwise, it forwards the request to the MC.

The remainder of this chapter is organized as follows. A cognitive routing protocol for software-defined vehicular networks is proposed in Section 5.2. Section 5.3 discusses simulation performance results, while Section 5.4 concludes the chapter.

5.2 Proposed cognitive routing protocol for SDVN

A cognitive routing protocol for software-defined vehicular networks is proposed in this chapter. The objective of this novel routing protocol is to overcome major issues in existing vehicular communications that leads to deterioration of network performance. This chapter

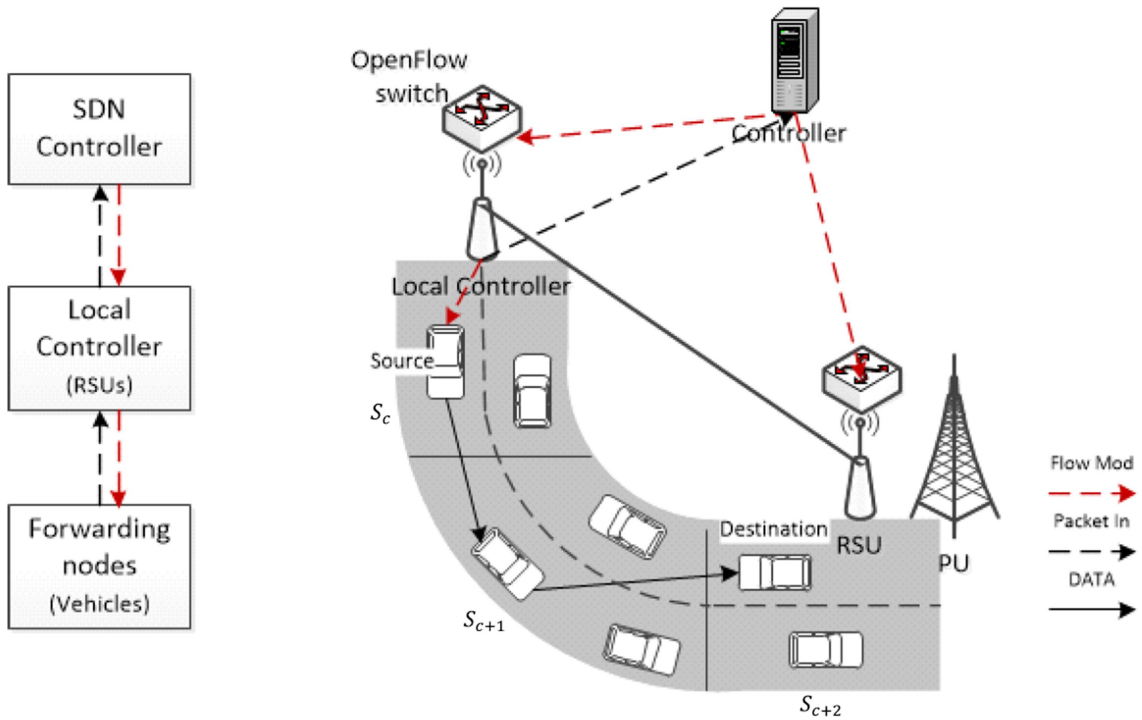


Figure 5.1: Cognitive radio software-defined vehicular network (CR-SDVN).

intends to solve the problems of spectrum scarcity, intermittently connected networks, high latency, and large amounts of overhead. This work combines a cognitive capability with a routing technique in vehicular networks by using SDN as a new candidate to improve network performance and communications reliability. The aim here is to find a stable route between source and destination by jointly selecting the channel and relay node in an efficient and reliable manner.

A cognitive radio software-defined vehicular network with V vehicles, L LCs, and an MC, is considered as shown in Fig. 5.1. PUs are assumed to be sited along the roadways. Each road is divided into several segments of equal length, l. We assume that channel state (presence or absence of the PU) is the same for each segment. Vehicles only communicate with each other if they have consensus about a common idle channel. Keeping the channel

state the same for each segment helps the vehicles to establish stable links, as they can easily communicate with each other due to having common idle channels within a segment. Similarly, each RSU and vehicle can only establish a communications connection if they both have consensus about a common idle channel. To sense the spectrum for each segment, we apply a BP algorithm to make a final belief about the channel state by exchanging the local beliefs of all neighboring vehicles within communications range of each other. Local beliefs are computed by spectrum sensing based on an energy detector scheme.

The MC is responsible for keeping global, updated information about the network topology, and it helps the network to provide the best stable route by maximizing the path duration among all the paths between source and destination. Those RSUs that serve as LCs reduce the burden of the MC by keeping local, updated information about the network topology within communications range. Because a network may consist of hundreds of nodes, it is inappropriate for a single controller to control the whole network, particularly when the nodes are highly dynamic. For that reason, we assume that vehicles periodically update each other and the corresponding RSUs about their current state while moving. Hence, the MC cooperates with LCs to maintain the global network topology. When a request packet reaches any LC, the LC checks its flow table for a path to the destination. It quickly responds to the requesting vehicle without sending a packet to the MC if it finds a path to the destination in its flow table.

The algorithm has two phases: the registering phase and the route prediction phase. As there are several RSUs in the network, the first objective is to select which one will function as an LC and by which measure it will announce itself as an LC. In view of that, RSUs apply a tree-based approach (see Fig. 5.2) to locate each other at different depths and to select one at each depth as the LC. Accordingly, in the first phase, selected RSUs register themselves with the MC as LCs. The selection of LCs is done just for that

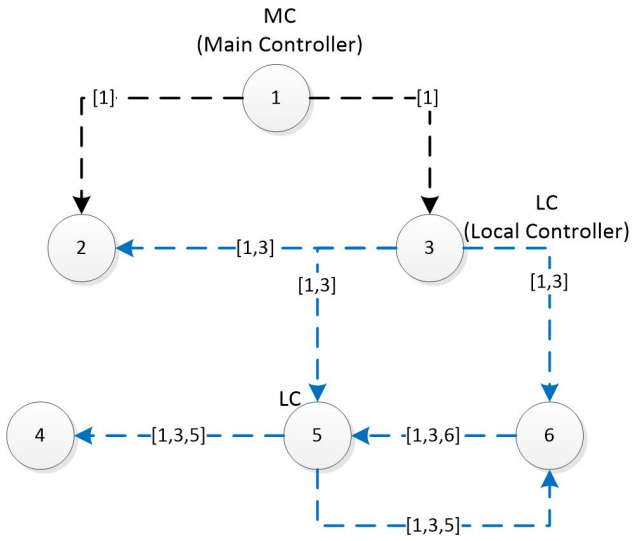


Figure 5.2: Selection criterion of LCs.

one time at the start of the protocol, because RSUs are fixed nodes. Once the selection is done, the protocol switches to the route prediction phase. In the following, we will discuss each phase in depth.

1. **Registering phase**: The road trajectory has several RSUs that are in different positions from each other. We apply a tree-based approach to select the LC at each depth in this proposed scheme. The MC is considered a root node, and all RSUs are reflected as leaf nodes, as shown in Fig. 5.2. These leaf nodes at different depths form several layers from the MC. RSUs at the same depth exchange control messages with each other and select one RSU as the LC. The registering phase is divided into the following four steps.

   Step 1: The MC first sends a request message to all RSUs within communications range in order to get the network topology. This message is a control message, i.e. a Hello message. As shown in Fig. 5.2, only nodes 2 and 3 are within communications range of the MC; therefore, these nodes first receive this message.

Step 2: Each RSU receiving the message calculates its delay using (5.1) below and compares it with the neighboring RSUs at the same depth. The RSU having the minimum delay at that depth announces itself as the LC:

$$Delay = (T_p + T_r + EVC)HopCount \tag{5.1}$$

where propagation delay $T_p = \frac{d_{MC,j}}{a \times speed}$, transmission delay $T_r = \frac{P_s}{C_{MC,j}}$, and expected vehicular count $EVC = \frac{1}{\left(hello\ messages/t\right)}$; $d_{MC,j}$ is the distance between the MC and each j RSU (i.e. $\sqrt{(x_{MC} - x_j)^2 + (y_{MC} - y_j)^2}$, a is a constant, *speed* is the speed of light, P_s is packet size, $C_{MC,j}$ is link capacity between the MC and j, and t is the time in the previous few seconds. The number of Hello messages in the previous few seconds can be calculated by RSUs as the vehicles periodically update each other and the nearby RSUs with their current state while moving. This parameter helps in improving network stability by avoiding sparse network conditions, thereby selecting the LC that has high connectivity. $HopCount$ is calculated by the number of layers and RSUs that a message has to travel through to reach the MC (see Fig. 5.2).

Step 3: The selected LC (i.e. node 3) advertises a reply message to the MC and all neighboring RSUs, as shown in Fig. 5.2, with the updated network information of all its neighboring nodes (vehicles and RSUs). All the nodes receiving this message save the route to the MC in their flow table.

Step 4: The first three steps are repeated at every depth and, last of all, the MC establishes the global topology for all the LCs, RSUs, and vehicles in the network.

At the conclusion of this phase, the selection of LCs provides a localized global view at each depth from the MC. Hence, different types of controller in this proposed scheme

are used to reduce the network burden from the single main controller and to reduce overall overhead and delay.

2. **Route prediction phase**: Once all the LCs are selected, the protocol switches to the route prediction phase. The foremost part of this cognitive routing scheme that makes it efficient is the estimation of path duration between source and destination. Because this is an SDN-based cognitive routing scheme, the controllers are responsible for providing the best stable route between source and destination by jointly selecting channel and relay. We all know that vehicle density on different roads is different. Some roads are busy, having high connectivity, and hence, make stable links, whereas others are sparse, forming fragile links, thereby degrading network performance. In the same way, the possibility of a vehicle establishing a link with any RSU/LC also depends on vehicle density. As a result, there are two cases: the source vehicle outside communications range of any RSU/LC, and the source vehicle within communications range of any RSU/LC.

   Case 1 (Source outside communications range): If a source vehicle is moving outside the communications range of any LC, it finds the next-hop node to reach the nearby LC in a way similar to conventional routing. It sends a beacon message to all its neighboring nodes. The beacon message includes ID, position, velocity, and channel state. The neighboring nodes within communications range of the source vehicle send back a reply with their updated information. The source then calculates the link duration prediction (LDP) for each neighboring vehicle to find the best relay node. LDP_{ij} is calculated between two vehicles to reach the LC as follows:

$$LDP_{ij} = \frac{r \pm d_{ij}}{\sqrt{(v_i \cos\theta_i - v_j \cos\theta_j)^2 + (v_i \sin\theta_i - v_j \sin\theta_j)^2}} \times min(Ch_1, Ch_2, ..., Ch_M) \tag{5.2}$$

where v is velocity, θ is the angle, d_{ij} is the distance, and r is the transmission range; $min(Ch_1, Ch_2, ..., Ch_M)$ represents the channel that has the highest belief in a set of idle channels between vehicle i and vehicle j, which will be explained in detail in the next subsection.

Among all the neighboring vehicles within communications range of the source node, the source vehicle selects the one that has the minimum LDP. Therefore, the best relay node is calculated as:

$$min(LDP_1, LDP_2, ..., LDP_N) \tag{5.3}$$

where N is the total number of neighboring nodes within communications range of the source node. In so doing, the source vehicle selects the relay node hop-by-hop and finally reaches the LC. Once it establishes a route to the LC, the LC checks its flow table for whether it has a route to the destination or not. If the LC does not find a route to the destination, it sends the request packet (*packet-in*) to the MC to find the best stable route to the destination.

Case 2 (Source within communications range): When a source vehicle is moving within communications range of an LC, it directly sends the request packet (*packet-in*) to the LC. The LC checks its flow table to determine if it has a route to the destination, and it sends a reply message with the best route to the destination. If it does not find a match, it forwards the request packet to the MC. Either the MC or the LC estimates the best stable route in the following manner. Any controller first calculates the path duration of all paths, P, from the source to the destination in the network. The path duration (PD) is calculated as

$$PD_p = min(LDP_{1,p}, LDP_{2,p}, ..., LDP_{Th,p}) \tag{5.4}$$

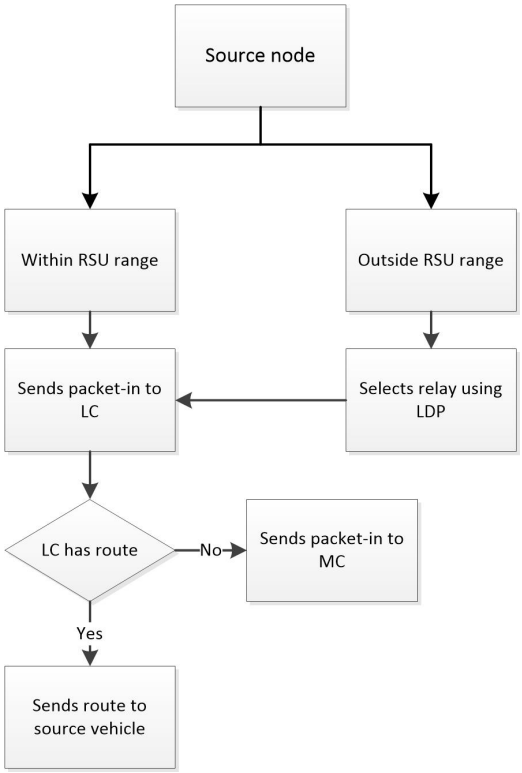


Figure 5.3: A flowchart representing two cases of a source node receiving an updated route from controllers.

where $p = 1, 2, ..., P$ is the total number of paths between source and destination, and Th is the total number of hops for each path between source and destination. Finally, any controller (MC or LC) finds the best route, R, to the destination as follows:

$$R = max(PD_p) \tag{5.5}$$

The source node, after receiving the best route, starts transmitting data. As this is a cognitive routing scheme, maximizing the path duration enhances the stability of the network. This final route is based on the path duration (i.e. how long a link is stable between two communicating vehicles). If any intermediate node fails to sustain stability, it repeats the above procedure to reach a nearby LC without sending the request packet back to the source node. Consequently, the SDN approach reduces

delay by reducing the number of control messages. Fig. 5.3 explains the comprehensive algorithm by showing how the source selects the LC and communicates with the MC to find the final route that maximizes path duration from among all the paths between source and destination.

5.2.1 Channel selection using belief propagation

This subsection explains how vehicles sense the idle spectrum and exchange their local sensing results with each other and with nearby RSUs. Each vehicle periodically senses the spectrum for each road segment while moving, and stores the result in its sensing table. BP [31] is an algorithm that computes the marginal probabilities (i.e. beliefs) by iteratively exchanging local messages. Likewise chapter 2 and 3, the first step of this algorithm is to find local sensing results. Each vehicle performs spectrum sensing using an energy detector scheme to detect the presence of the PU on the road segments. PUs are incumbent users that can be passengers in vehicles, or can be other users located in buildings, restaurants, etc., alongside the road utilizing other licensed bands, such as TV bands (VHF and UHF), Wi-Fi, etc. [26,27]. We consider the cognitive radio spectrum as TV spectrum in this work, and we divide the TV band into M channels where PU activity is modeled as exponential on/off activity pattern. Spectrum sensing is done by each vehicle, as in the following binary hypothesis model:

$$x_{i,S_c}(t) = \begin{cases} n_{i,S_c}(t), \quad H_0 \\ \\ s_{i,S_c}(t) + n_{i,S_c}(t), \; H_1 \end{cases} \tag{5.6}$$

where $i = 1, ..., V$, S_c represents the current segment, $s_{i,S_c}(t)$ is the PU signal received by vehicle i in the current segment, S_c, and $n_{i,S_c}(t)$ is additive white Gaussian noise (AWGN).

The energy-based test statistic is given as follows:

$$x_{E_i} = \sum_{g=1}^{B} |x_i(g)|^2 \tag{5.7}$$

where B is the time–bandwidth product, and $x_i(g)$ is the gth sample of the received PU signal at vehicle i.

Each vehicle calculates its local decision as an a posteriori probability, which is given as:

$$\varphi^f_{i,S_c}(H_h) = P(H_h|x_{i,S_c}) = \frac{P(x_{i,S_c}|H_h)P(H_h)}{P(x_{i,S_c})} \tag{5.8}$$

where $f \in M$, $P(x_{i,S_c}|H_h)$ is the probability density function of normally distributed random variable x_{i,S_c} conditioned on $H_h, (h = 0, 1)$, $P(x_{i,S_c})$ is the normalizing constant, and $P(H_h)$ is the prior probability, which is assumed to be constant for all vehicles. To calculate a belief about the state of vehicle j in segment S_{c+1} estimated by vehicle i in segment S_c, vehicles i and j within communications range of each other exchange their messages as:

$$\mu^f_{(i,S_c)(j,S_{c+1})}(H_{j,S_{c+1}}) = w \sum_{H_{i,S_c}} \psi^f_{(i,S_c)(j,S_{c+1})}(H_{i,S_c}, H_{j,S_{c+1}})\varphi^f_{i,S_c}(H_{i,S_c}) \prod_{k\in(N_i-\{j\})} \mu^f_{(k,S_{c-1})(i,S_c)}(H_{i,S_c}) \tag{5.9}$$

$\mu^f_{(i,S_c)(j,S_{c+1})}(H_{j,S_{c+1}})$ describes the belief about the state of vehicle j in segment S_{c+1} estimated by vehicle i in segment S_c, w is the weighting factor, the term $k \in (N_i - \{j\})$ describes how k only belongs to the neighbors of i and not the neighbors of j, S_{c-1} represents the vehicles in all the previous segments that are connected to vehicles in S_c, and $\psi^f_{(i,S_c)(j,S_{c+1})}(H_{i,S_c}, H_{j,S_{c+1}})$ is a compatibility function, which is defined as:

$$\psi^f_{(i,S_c)(j,S_{c+1})}(H_{i,S_c}, H_{j,S_{c+1}}) = \begin{cases} \eta & if\ H_{i,S_c} = H_{j,S_{c+1}} \\ 1-\eta & if\ H_{i,S_c} \neq H_{j,S_{c+1}} \end{cases} \tag{5.10}$$

The compatibility function depends on the correlation between states H_{i,S_c} and $H_{j,S_{c+1}}$. By changing the value of η, we control the correlation among vehicles. The larger the value of η, the more the correlation between neighboring vehicles and hence, the higher the detection accuracy. Therefore, correlation among sensing data from different vehicles enhances detection accuracy [27].

Finally, the belief of each vehicle moving in its current segment S_c is calculated as:

$$b^f_{i,S_c}(H_{i,S_c}) = w\ \varphi^f_{i,S_c}(H_{i,S_c}) \prod_{k\in(N_i)} \mu^f_{(k,S_{c-1})(i,S_c)}(H_{i,S_c}) \tag{5.11}$$

On the basis of these beliefs, each vehicle makes the final decision about each segment and channel as follows:

$$D^f_{i,S_c} = \begin{cases} H_0 & if\ b^f_{i,S_c}(H_0) > b^f_{i,S_c}(H_1) \\ \\ H_1 & if\ b^f_{i,S_c}(H_0) < b^f_{i,S_c}(H_1) \end{cases} \tag{5.12}$$

Now the term $min(Ch_1, Ch_2, ..., Ch_M)$ in (5.2) is defined as the channel that has the highest belief among all the beliefs for a set of idle channels, where the value of Ch_{f^*} for idle channel $f^*(f^* = 1, ..., M)$, between vehicle i and vehicle j is calculated as $Ch_{f^*} = 1 - min\left(b^{f^*}_{i,S_c}(H_0), b^{f^*}_{j,S_{c+rs}}(H_0)\right)$; rs represents a range size that can be any segments within transmission range of vehicle i moving in segment S_c.

5.3 Simulation results and discussion

We evaluated the performance of this proposed scheme in NS-2 using the module for cognitive radio ad hoc networks. We divided the road into 20 equal segments, S, each 100 m in length, l. The spectrum band was divided into $M = 5$, and each channel could be occupied by a licensed PU. The number of PUs was three, each having a transmission range

of 500 m. These PU nodes were fixed nodes that were other than the relay nodes and their activity was modeled as exponential on/off activity pattern with rate parameter 0.05. The number of RSUs used was two at each depth, each having a transmission range of 350 m, and there was a total of three layers at different depths from the MC. The number of MCs is 1, packet size $P_s = 64$ bytes, and $a = 2/3$ [105]. With a value of $\eta = 0.9$, vehicles moved at varying speeds from 10m/s to 25m/s. The number of relay nodes varied between 5 and 30, each having a transmission range of 250 m. Our simulation results are the average of more than 70 runs.

The study considers both V2V and V2I communications. As this is a cognitive routing scheme, the radio channel can be affected by both small-scale and large-scale fading. Accordingly, there is no line-of-sight path between the primary transmitter and the secondary receiver, resulting in a composite of various multipath components of received signals [37, 38]. In consequence, this degrades the sensing performance. To overcome this problem, we considered a *Nakagami* distribution to model the fading of PU activity on the performance of the energy detector-based spectrum sensing scheme, as this type of distribution describes the statistical characteristics of both small-scale and large-scale fading [38].

As argued in section 5.1, there is no publicly known cognitive routing protocol for a CR-SDVN that combines a cognitive capability with a routing technique by using the SDN approach. Therefore, we chose to compare this proposed scheme with the SDN-based routing protocol called the hierarchical software-defined VANET (HSDV) [100]. In this scheme, the controller is responsible for choosing next hops by making links based on the closest distance to the destination. However, our proposed scheme estimates the path duration in finding stable links, and then selects the best route by maximizing the path duration. Another reason for choosing HSDV is that both schemes reduce the burden on the main controller by using several local controllers to maintain a localized view of

the network topology. Furthermore, in order to make HSDV a cognitive routing scheme, we simulated it in combination with the channel selection scheme proposed by Abbassi *et al.* [26] and refer to it as the reference scheme with SDN. To evaluate the impact of utilizing controllers in our proposed scheme, we made another comparison with a cognitive routing scheme–expected path duration maximized routing (EPDM-R) [29] which does not consider SDN, and we refer to it as the reference scheme without SDN. This scheme is similar to AODV, which selects the best route from source to destination from among all attainable paths. Three metrics are used to evaluate the performance of our proposed scheme: (a) end-to-end delay, (b) packet delivery ratio, and (c) routing overhead ratio.

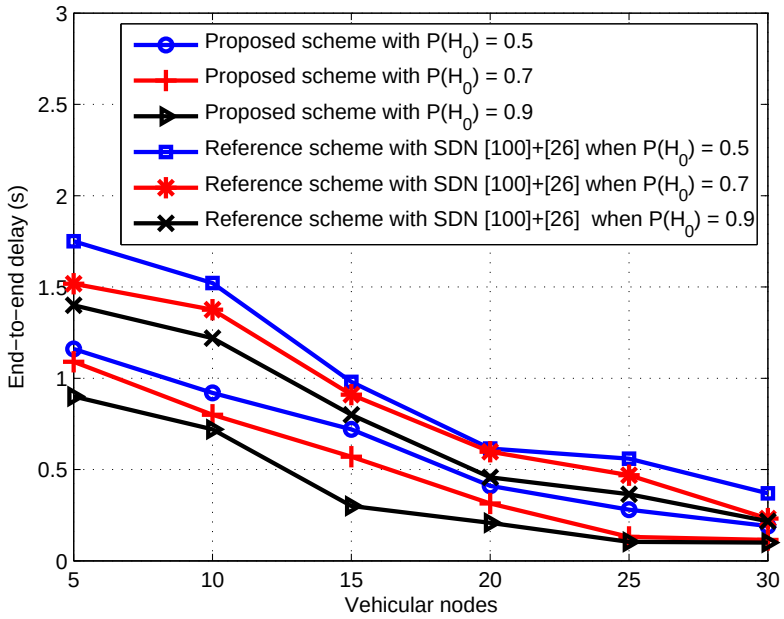


Figure 5.4: Performance comparison between two SDN-based schemes in terms of end-to-end delay.

Figures 5.4 and 5.5 show the performance of end-to-end delay as a function of the number of vehicles, with different probabilities of the PU being idle as a parameter. Fig. 5.4 and 5.5 show a comparison of this proposed scheme with the SDN-based and

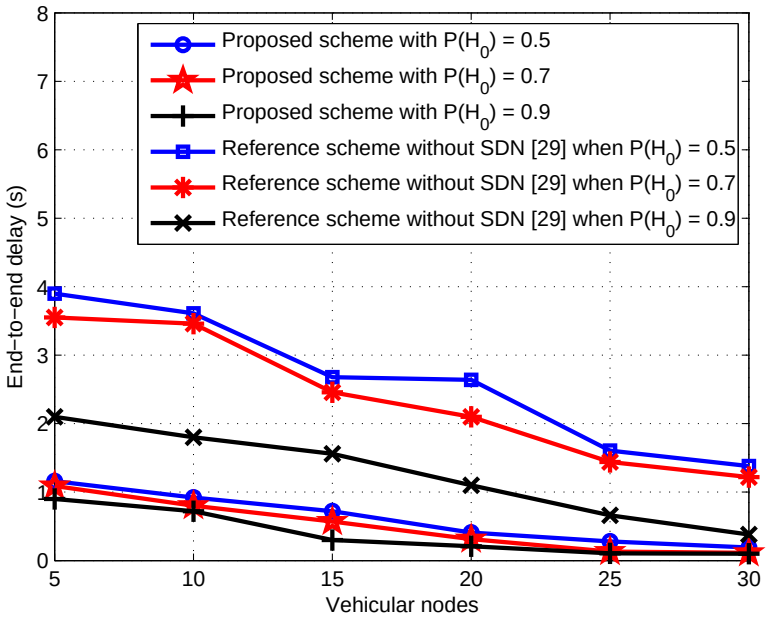


Figure 5.5: Performance comparison between SDN and non-SDN schemes in terms of end-to-end delay

non–SDN-based reference schemes, respectively. With an increasing number of vehicular nodes in the network, the delay decreases. The pattern is the same for all the schemes, i.e. when increasing the number of vehicular nodes and increasing the probability of the PU being idle, delay decreases. This is because the connectivity in the network increases with an increase in vehicular nodes, and for the latter case, the high probability increases the chance of more idle channels in the network. When the network is sparse (between 5 and 15 nodes), the delay is high for all the schemes. This is because the querying node does not find any other node to make a stable link, under sparse network conditions, and therefore incurs a large delay. However, in this proposed scheme, considering the RSUs at different depths allows them to serve as relay nodes, even in sparse network conditions. Also, selecting the local controllers in the proposed scheme further reduces the delay. When these LCs know the route to the destination, they reply to the querying nodes with the

updated route without communicating with the MC, and thereby reduce network delay. Hence, our target in this chapter is to maintain network stability by providing the best route between source and destination. For that reason, this proposed scheme shows less delay, compared to both reference schemes. The reference scheme in Fig. 5.4 selects the next node based on distance only, whereas the proposed scheme in this chapter calculates the link duration, which includes both speed and direction of vehicles. In the reference scheme of Fig. 5.5, each node selects its next relay node to form a stable link, hop-by-hop, which incurs a large delay in the network; in this proposed scheme, each querying node directly makes a connection with the controller to get a stable route. Both Fig. 5.4 and Fig. 5.5 show that decreasing the idle probability decreases network performance. This is from facing the difficulty in finding a common free channel when the idle probability of the PU decreases. In comparisons with other spectrum-sensing techniques, the BP algorithm in this proposed scheme outperforms the spectrum sensing approach of the reference schemes. The BP algorithm enhances the accuracy of hypotheses concerning spectrum availability, and therefore, the overall performance of this proposed scheme in terms of delay is better than the other two schemes.

Figures 5.6 and 5.7 show the performance of packet delivery ratio as a function of the number of vehicles, with different probabilities of the PU being idle as a parameter. The packet delivery ratio for both the proposed and reference schemes increases with an increasing number of vehicles in the network. The SDN approach improves network performance in terms of delivery ratio because of the logically centralized controller that dictates the behavior of the network. In the reference scheme without SDN, a querying node has to select the next node for every hop until it reaches the destination. By doing so, it may come across several fragile links due to the highly dynamic nature of vehicular nodes. Correspondingly, for every unstable link, the scheme needs to update all the nodes

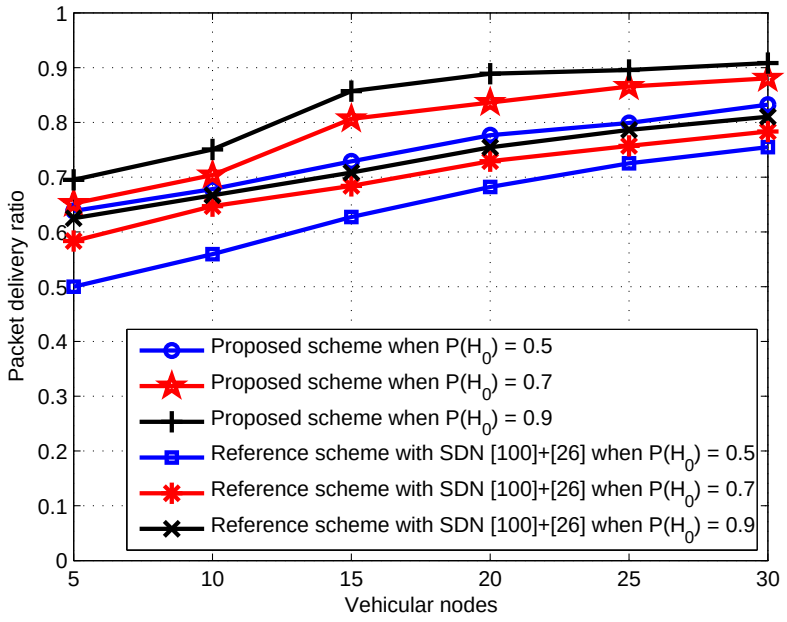


Figure 5.6: Performance comparison between two SDN-based schemes in terms of packet delivery ratio.

between source and destination as to the current network state. However, in the proposed scheme of this chapter, the MC keeps the global view of the network, which means the MC manages all the information about idle channels and relay nodes for each segment on the road. Therefore, by calculating the path duration, the MC provides the best stable route between source and destination to each querying node. Furthermore, in any case of an unstable link due to the unavailability of any vehicle or channel, the querying node directly asks the MC for a route update without sending the packet back to the source node. Hence, this proposed scheme increases network stability by providing more-stable routes, which increases the packet delivery ratio. Fig. 5.6 shows that this proposed scheme outperforms the reference scheme with SDN; nevertheless, both are SDN-based schemes. The reason is the difference in the selection of the route between source and destination. Selecting the nearest vehicle to the destination (based on distance) only makes more sporadic links,

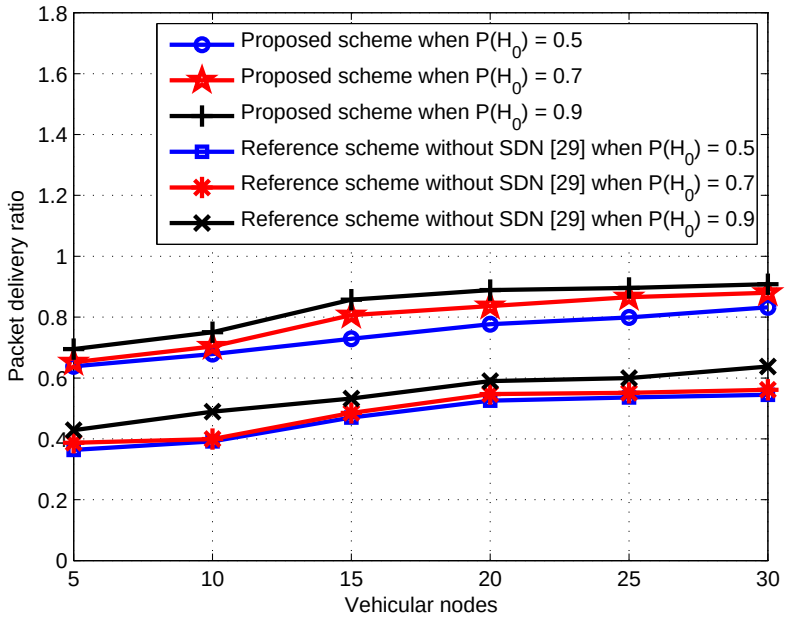


Figure 5.7: Performance comparison between SDN and non-SDN schemes in terms of packet delivery ratio.

which decreases the successful delivery of packets. Both Fig. 5.6 and 5.7 also show that when increasing the idle probability of the PU, the packet delivery ratio increases for all the schemes. The reason is the same; the number of free channels increases with the high probability. When the idle probability is low, there are fewer chances for vehicles to make a stable link, because they do not find consensus about a common free channel. A low probability means that if a vehicle finds another node, it may not select it as a relay node due to not finding a common channel between the two, thereby decreasing the chance for vehicles to communicate with each other. As a result, the performance degrades when the idle probability of the PU decreases.

Figures 5.8 and 5.9 show the performance of routing overhead ratio as a function of the number of vehicles, with different probabilities of the PU being idle as a parameter. From the figures, it can be seen that the routing overhead ratio increases with an increase in the

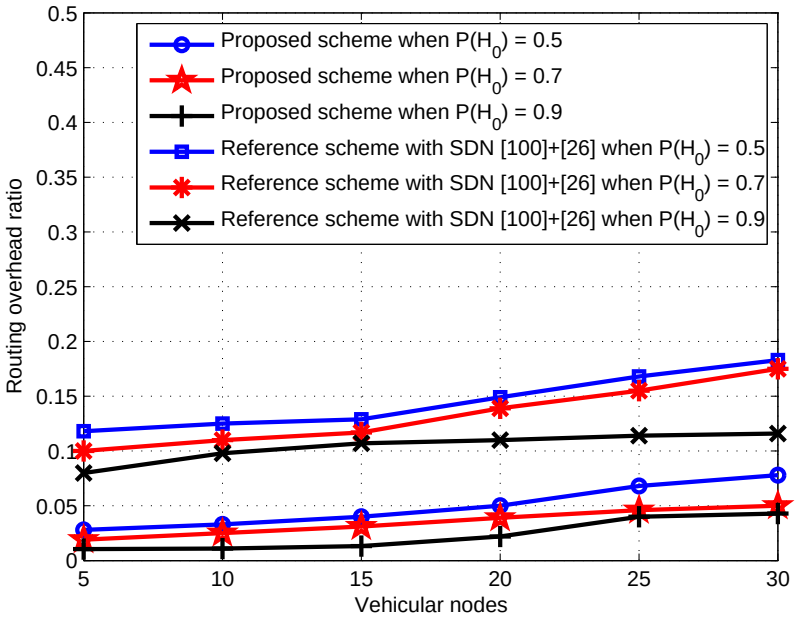


Figure 5.8: Performance comparison between two SDN-based schemes in terms of routing overhead ratio.

number of vehicles and with a decrease in idle probability under the proposed and reference schemes. However, the overhead ratio of SDN-based schemes shows better performance than the non–SDN-based approach. This is due to the logically centralized controller, which reduces the number of control messages in the network. Each querying node in the SDN-based scheme communicates with the controller (either MC or LC) whenever it encounters a packet mismatch or it requires any route update. However, in the non–SDN-based approach, the querying node sends beacon messages to all the neighboring nodes for each update about the current network state. Consequently, with a higher number of vehicles, the message update rate is also high. The proposed scheme in this chapter outperforms both the reference schemes. The reason for the better performance is the main controller, which keeps a global record of updated information due to the cooperation among the LCs and vehicles. Also, the selection of LCs at different depths from the MC reduces unnecessary

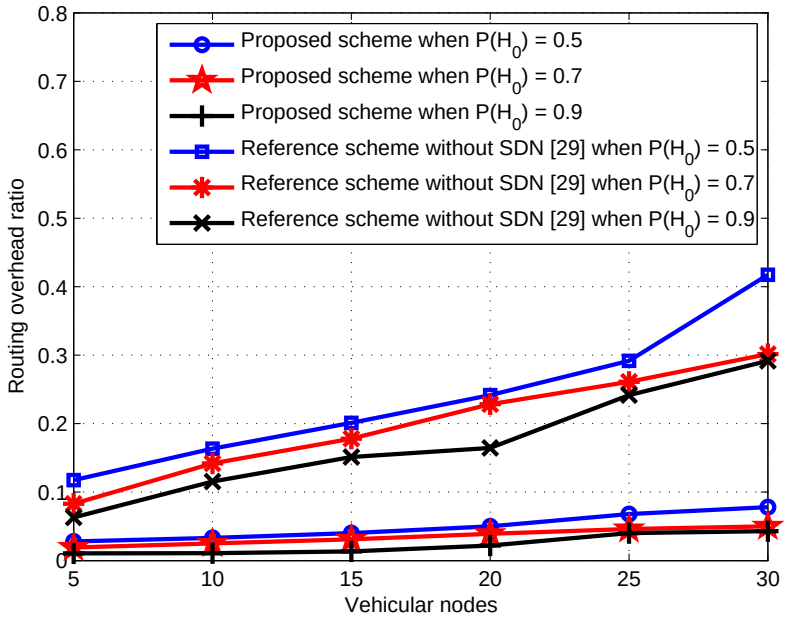


Figure 5.9: Performance comparison between SDN and non-SDN schemes in terms of routing overhead ratio.

control messages, thereby reducing the total control overhead. Moreover, selecting the most stable route between source and destination at the controllers by maximizing the path duration reduces overall network overhead. On the other hand, the distance-based selection in the reference scheme with SDN shows performance degradation in terms of overhead ratio, as the stability is not assured. Fig. 5.8 and 5.9 also show that decreasing the idle probability of the PU increases the overhead ratio. This means that the channel is occupied by the licensed user for a long time. Hence, vehicles have fewer chances of finding a common idle channel, and thus, the message exchange rate among vehicles increases in order to find an idle channel. A complete analysis of the simulation results in this chapter show that SDN-based schemes outperform the non–SDN-based scheme, and this proposed scheme outperforms the two reference schemes. Also, decreasing the idle probability of the PU decreases network performance.

5.4 Chapter summary

In this chapter, a novel routing protocol for cognitive radio software-defined vehicular networks is proposed. The idea of combining a cognitive capability with a routing scheme in software-defined vehicular networks makes this protocol unique. The protocol has two phases: the registering phase and the route prediction phase. A main controller is responsible for network management, while several local controllers are selected at different depths from the main controller to reduce the number of control messages and any network delay. The local controllers are RSUs along the roadside that are selected in the registering phase. In the route prediction phase, the controllers are responsible for providing a stable route to the querying node by maximizing the path duration among all the paths between source and destination. A link is formed between two nodes if they both have consensus about a common idle channel. Therefore, spectrum sensing is performed based on a belief propagation algorithm to find common free channels. The results in this chapter show better performance for end-to-end delay, packet delivery ratio, and routing overhead ratio.

Chapter 6

Software-Defined Cognitive Maritime Networks

6.1 Introduction

With the development of the marine industry and an increase in the number of marine users, there is an essential need for a high-speed and low-cost maritime communications system that provides ubiquitous stable links among users aboard ship. As discussed in chapter 3, current maritime communications systems are based on high frequency (HF), very high frequency (VHF), and ultra-high frequency (UHF) radios, which have been found insufficient to deal with the developing requirements of maritime applications [7]. Likewise, satellite links are used as an alternative to maintain the stability of the network under sparse conditions far out at sea. But using a satellite service is still a hurdle because of its high maintenance and replacement cost, high latency, and high-cost data rate [106]. To address these issues, this chapter intends to apply SDN in the marine environment in order to overcome the shortcomings of existing architectures in marine networks. SDN is applied

for the first time using a combination of a cognitive capability and a routing technique in order to overcome the problems of limited services altogether due to the high cost of satellite links, spectrum scarcity, and high latency.

Routing in cognitive maritime networks is more challenging than conventional routing protocols in maritime networks. AODV protocol was used [107] to minimize undesirable effects of the marine environment by considering the relationship between sea waves and received signal strength in order to avoid the use of unstable links in maritime wireless networks. Wen *et al.* [108] investigated a multiple-ship routing and speed optimization problem adhering to time, cost, and environmental objectives. This is the first paper in the maritime literature that addresses a multiple ship scenario in which fuel price, the market freight rate, the dependency of fuel consumption on payload, and the cargo inventory costs were all taken into account to provide useful insights into a balanced economic and environmental performance. Wu *et al.* [109] employed opportunistic routing for maritime search-and-rescue wireless sensor networks to make the best use of the broadcast property in radio propagation. To maintain the latest neighbor information and minimize the energy cost of collecting this information, they proposed a lightweight, time series–based routing metric prediction method. Kessab *et al.* [110] provided a new tool for predictions about the satellite–terrestrial station in a hybrid satellite–maritime mobile ad hoc network. Their results demonstrated that end-to-end propagation delays can be efficiently reduced by the deployment of hybrid stations.

None of these routing protocols for maritime networks considered spectrum scarcity issues caused by limited communications frequencies. Proposing a cognitive routing protocol that takes the spectrum scarcity issue into account is essential in order to meet the increasing demands of marine users. Due to the lack of broadband wireless networks at sea, Zhou *et al.* [111] envisaged worldwide interoperability for microwave access (WiMAX)

mesh networks for high-speed and low-cost ship-to-ship communications. The scheme used WiMAX to overcome the issues of wireless networking in a marine environment, however, the cooperative cognitive maritime cyber-physical system (CCMCPS) [112] is an innovative paradigm that achieved high-speed and low-cost communications services for the cognitive maritime community. It was envisioned that the cyber-physical systems that incorporate information communications technology and sensing-enabled vessels could impose new opportunities, applications, and agendas as well as challenges for the maritime community. A biologically inspired cooperative spectrum sensing scheme (BIC3S) [113] is another mechanism to deal with the reliability and energy consumption challenges associated with the marine environment. Zhang *et al.* [106] studied the problem of effectively allocating the spectrum to SUs with different priorities in a maritime cognitive radio communications system. Another hybrid satellite–terrestrial communications system aimed at the fifth generation (5G) [114] was proposed to discuss several key issues in applying CR to future 5G satellite communications.

Similarly, research in software-defined maritime networks is still in its infancy. Nazari *et al.* [115] proposed a multi-path transmission control protocol (MPTCP) based on a SDN framework for a fleet of naval ships that rely on multiple satellite communications systems. A new software-defined wireless network (SDWN) architecture was proposed [116] to enable high performance in the next generation of ship-area networks based on self-organizing time division multiplexing access. Nobre *et al.* [117] were the first to integrate battle networking (BN) with SDN and established a software-defined battle networking (SDBN) architecture to get more flexibility and programmability in network-centric operations. The authors envisioned the SDBN controller being viewed as a military SDN exchange that integrates different SDN controllers, considering specific communications technologies. Yang *et al.* [95] integrated SDN and fog computing into a maritime wideband communi-

cations system to minimize total weight tardiness for a single-machine scheduling scenario in order to achieve a minimized delay of weighted uploading packets. All the studies cited above for software-defined maritime networks developed schemes by utilizing satellite communications to improve the performance of maritime networks. This chapter proposes a scheme that combines a cognitive capability and a routing technique without using satellite communications (because of its high cost and latency) in software-defined maritime networks.

The goal is to select the best route between source and destination that maximizes the path duration among all the paths. This chapter intends to overcome the problems of spectrum scarcity, intermittently connected networks, high latency, and the large overhead in cognitive maritime networks by implementing a novel cognitive routing protocol for cognitive radio software- defined maritime networks (CR-SDMNs). The SDN controllers programmatically configure the traffic by keeping a global view of the network. This proposed scheme has a single MC on land close to the seashore, and several LCs that serve as cluster heads (CHs) are in different locations at sea. CHs keep a localized view of the network by collecting information within each cluster. For inter-cluster communications, autonomous surface vehicles (ASVs) serve as gateways for relaying data between distant nodes. Ships send requests to CHs, querying for a route to the destination. The CH quickly responds to the request if it has a route to the destination; otherwise, it forwards the request to the MC.

The remainder of this chapter is organized as follows. In Section 6.2, a cognitive routing protocol for software-defined maritime networks is proposed. Section 6.3 discusses simulation performance results, while Section 6.4 concludes the chapter.

6.2 Proposed cognitive routing protocol for software-defined maritime networks

A cognitive routing protocol for software-defined maritime networks is proposed in this chapter. The objective of this novel routing protocol is to overcome major issues in existing maritime communications that lead to deterioration of network performance. This chapter intends to solve the problems of spectrum scarcity, intermittently connected networks due to constantly changing sea surfaces, high latency (especially due to satellite links), and large amounts of overhead. This work combines a cognitive capability with a routing technique in maritime networks by using SDN as a new candidate to improve network performance and communications reliability. Taking advantage of SDN, this chapter proposes that ships moving on a planned mission (e.g. naval fleets, courier missions, research missions) are considered a cluster. Each cluster head within a cluster performs the role of local controller (LC). This logically centralized controller is responsible to collect information of interest for any application in order to take full advantage of the whole network. This means that the ships working for one application within a cluster collect information from their surroundings and send the gathered data to the controller. The aim is to find a stable route between source and destination by jointly selecting the channel and relay node in an efficient and reliable manner.

A cognitive radio software-defined maritime network is shown in Fig. 6.1, where a source node in a cluster close to the seashore is looking for a stable route to a destination far out at sea and in a different cluster. The CR-SDMN considers S ships, C CHs, and one MC. Mobile ASVs improve network connectivity by relaying traffic under sparse network conditions. ASVs are used to collect and transport data among clusters (inter-cluster communication) as clusters are usually far away from each other (i.e. outside transmission

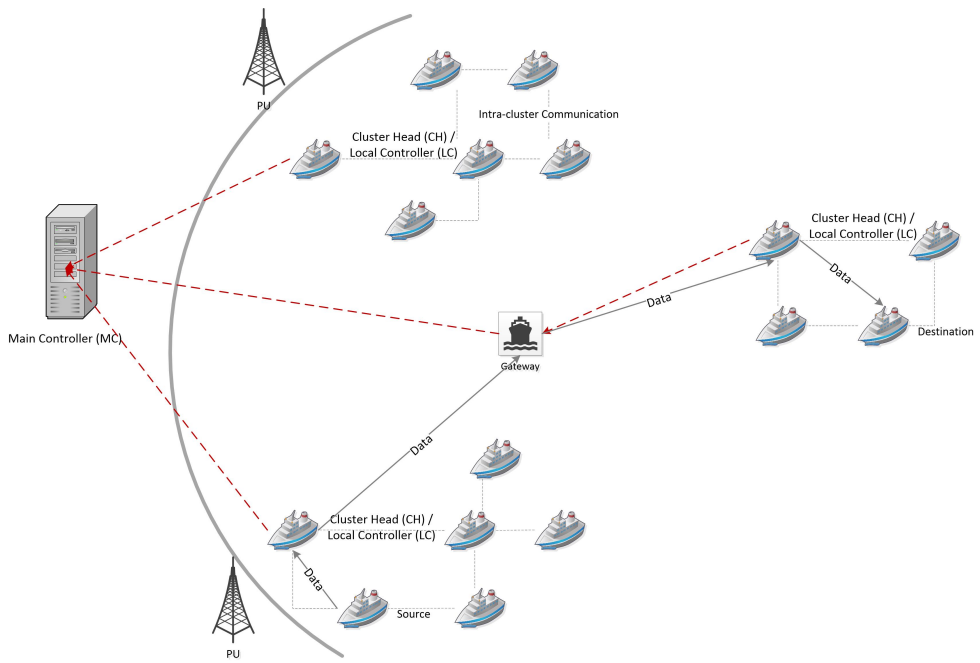


Figure 6.1: Cognitive radio software-defined maritime network (CR-SDMN).

range of any cluster member (CM) or CH) in the maritime network, and for communication to and from the MC (when CHs are far out at sea). ASVs move on fixed trajectories [118] where the track is maintained by the MC, and they identify themselves as gateways. PUs are assumed to be sited along the seashore, as shown in Fig. 6.1. This is a three-layered hierarchical network scheme where the first two layers (MC and CHs) communicate directly with each other only if the CHs are near the seashore. All the ships are moving, and therefore, for those CHs far out at sea, an ASV is used to collect and transport data to and from the MC, as shown in Fig. 6.2. The cluster members (ships) collect data from all neighboring nodes and send the gathered information to corresponding CHs (intra-cluster communication). All CHs share their localized view of the network with the MC (either directly or via ASV), such that the MC establishes a global network view.

The CHs reduce the burden of the MC by keeping local, updated information about

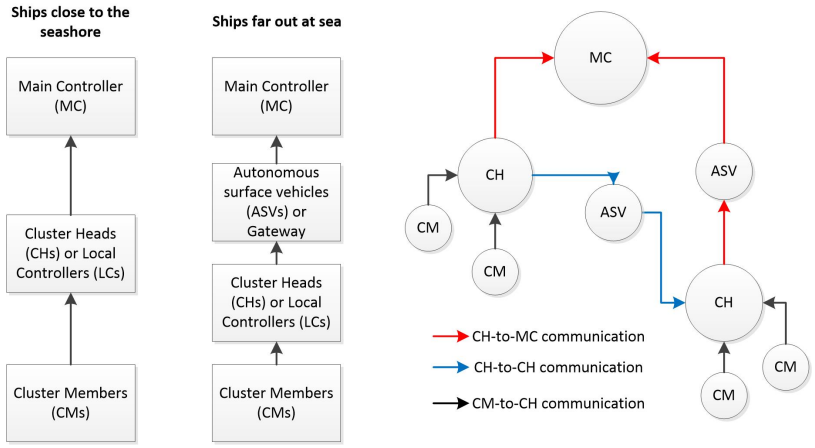


Figure 6.2: Inter- and intra-cluster communication for ships close to the seashore and far out at sea.

the network topology within their clusters. Generally, a fleet consists of hundreds of nodes; therefore, it is inappropriate for a single controller to monitor several ships moving on a specific mission in the network. For that reason, we assume that ships periodically update each other and their corresponding CH about their current state while moving. Hence, the MC cooperates with CHs to maintain the global network topology, and it helps the network provide the best stable route by maximizing the path duration among all the paths between sources and destinations. Ships only communicate with each other if they have consensus about a common idle channel. Likewise chapters 2, 3, and 5, in order to sense the spectrum, we apply a BP [31] algorithm to make a final belief about the channel state (the presence or absence of the PU) by exchanging the local beliefs of all neighboring ships within transmission range of each other (i.e. within a cluster). Local beliefs are computed by spectrum sensing based on an energy detector scheme. When a request packet reaches any CH, the CH checks its flow table for a path to the destination. It quickly responds to the requesting ship without sending a packet to the MC if it finds a path to the destination in its own flow table.

The protocol has two phases: beaconing and route estimation. In the beaconing

phase, each cluster selects its CH first, and the ones moving far out at sea select a gateway to make a connection with the MC. Each CM updates its CH with its current state, and each CH provides a localized overview of each cluster to the MC, which keeps global, updated information about the network. For simplicity, we assume that CMs must be one or two hops away from a CH, and each ship (either CH or CM) already has the exact position of the MC. Once the selection of CHs is done, the protocol switches to the route prediction phase. In the following, we discuss each phase in depth.

1. **Beaconing phase:** In the beaconing phase, all ships moving on a planned mission in a fleet select a CH by exchanging beacon messages with each other. The beacon message includes ship ID, position from the MC, and speed. The ships in a fleet move at a constant speed but are at different locations from the seashore. To make each cluster stable, we choose as the CH the one moving closer to the seashore. The CH should be the ship that incurs the lowest cost (i.e., has the highest stability and the more durable link with the MC) from among its neighboring ships in a cluster. Each ship calculates its cost (1/LD) using link duration (LD), compares it with other members of the cluster, and the ship with the minimum cost announces itself as the CH:

$$LD_{ij} = \frac{R \pm d_{MC,j}}{v} \tag{6.1}$$

where R is the transmission range, $d_{MC,j} = \sqrt{(x_{MC} - x_j)^2 + (y_{MC} - y_j)^2}$ and is the distance between the MC and each j ship, and v is the velocity of the ship. As the ships move, it is inappropriate to assume that all the clusters are moving closer to the shore. The ships far out at sea are unable to make a direct connection with the MC. Therefore, to make a stable network, we take advantage of the ASVs moving autonomously at sea with generally pre-programmed routes. Because there are several

ASVs in the network, the first objective is to select the one that will function as a gateway and by which measure the querying CH out at sea will announce it as a gateway. To make a stable connection for selecting the gateway node, the CH estimates the connection time (CT) [119] between itself and the moving ASVs and selects a gateway node that has the maximum CT:

$$CT = \frac{\triangle v_{CH,a} \times d_{CH,a} + \triangle v_{CH,a} \times R}{\triangle v_{CH,a}^2} \tag{6.2}$$

where $\triangle v_{CH,a} = \sqrt{(v_{CH}\cos\theta_{CH} - v_a\cos\theta_a)^2 + (v_{CH}\sin\theta_{CH} - v_a\sin\theta_a)^2}$, θ is the angle with respect to the MC, and a is any ASV.

Now, the CH of each cluster keeps the MC updated with the network topology of all members within a cluster. The CHs provide a localized overview of each cluster. In this way, any querying node, whenever it comes across link fragility, can ask the controller for an updated stable route to a destination without sending the packet back to the source node. Consequently, different types of controller in this proposed scheme are used to reduce the network burden on the single main controller and to reduce overall overhead and delay

2. **Route estimation phase:** Once the CHs and gateways are selected, the protocol switches to the route estimation phase. When a source node in any cluster wants to communicate with a destination node, it sends a request message to the controller. The foremost part of this cognitive routing scheme, which makes it efficient, is the estimation of path duration between source and destination. This is a challenging task for any source node in a maritime environment, especially when ships are far from each other and communications is continuously perturbed by sea waves. To make it possible, we apply the SDN technique so the controllers are responsible for providing the best stable route between source and destination by jointly selecting

both channel and relay. We know that some ships are close to the seashore, having high connectivity, and hence, make stable links, whereas others are far away, forming fragile links, thereby degrading network performance. Moreover, sea waves cause fluctuations in signal strength, which also results in several fragile links. For that reason, we form clusters and announce each CH as an LC. The two layers of controllers help the ships with the provision of stable links by keeping an updated network state.

The source directly sends a request packet to the CH. The CH checks in its flow table for a route to the destination, and sends a reply message if it has the best route to the destination. If it does not find a match, it forwards the request packet to the MC. Once the message reaches the controller, the CH/MC estimates the best stable route to the destination in the following manner. Any controller first calculates the path duration of all paths, P, between source and destination as follows:

$$PD_p = min(LET_{1,p}, LET_{2,p}, ..., LET_{Th,p}) \tag{6.3}$$

where $p = 1, ..., P$, Th is the total number of hops making up each path between source and destination, and link estimation time (LET_{ij}) is calculated as:

$$LET_{ij} = \frac{R \pm d_{i,j}}{\triangle v_{ij}} \times min(Ch_1, Ch_2, ..., Ch_M) \tag{6.4}$$

where $min(Ch_1, Ch_2, ..., Ch_M)$ represents the channel that has the highest belief among all the beliefs for a set of idle channels, where the value of Ch_{f^*} for idle channel $f^*(f^* = 1, ..., M)$ between ship i and ship j is calculated as $Ch_{f^*} = 1 - min\left(b_i^{f^*}(H_0), b_j^{f^*}(H_0)\right)$ (see (3.1) to (3.10)). Because two ships (either CM and CH, or CM and CM) can only communicate if they both have a common idle channel, the beacon message sent by a source node is an extended beacon message. This extended beacon message includes ID, position, channel state, and speed. Finally, the controller

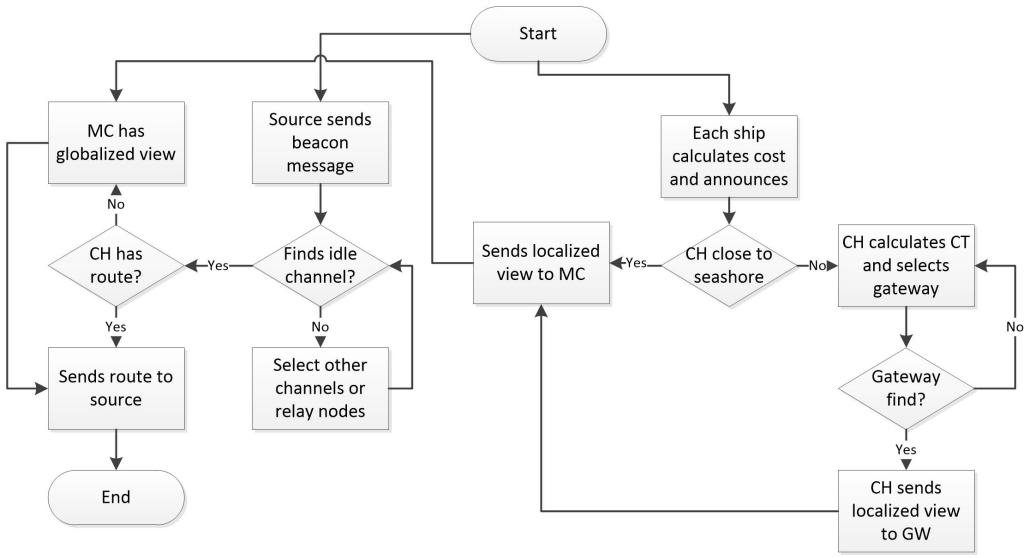


Figure 6.3: A flowchart representing the proposed algorithm.

finds the best route, $\hat{r}$, to the destination:

$$\hat{r} = max_{\hat{r} \in p}(PD_p) \tag{6.5}$$

The source node, after receiving the best route, starts transmitting data. As this is a cognitive routing scheme, maximizing the path duration enhances the stability of the network. This final route is based on the path duration (i.e. how long a link is stable between two communicating ships). If any intermediate node fails to maintain stability, it repeats the above procedure to reach a nearby CH without sending the request packet back to the source node. Consequently, the SDN approach reduces delay by reducing the number of control messages. Fig. 6.3 explains the comprehensive algorithm by showing how the ships first select the CH and then communicate, either with their corresponding CH or the MC, to find the final route that maximizes path duration from among all the paths between source and destination.

6.3 Simulation results and discussion

The performance of this proposed scheme is evaluated in NS-2 using the module for cognitive radio ad hoc networks. In this scheme, ships S were moving in three different clusters, each having a transmission range of 200 m. The speed of the ships within a cluster was constant. However, different clusters moved at various speeds up to a maximum of 15 m/s. Two ASVs were used, each moving at 20 m/s and having a transmission range of 300 m. The spectrum band was divided into $M = 5$, and each channel could be occupied by one of two licensed PUs, each having a transmission range of 500 m. These PU nodes were fixed nodes on land, and their activity was modeled as an exponential on/off activity pattern with rate parameter 0.05. One MC was on land close to the seashore. The number of ships varied from 10 to 35. The value $\eta = 0.9$ meant the two states H_i and H_j are highly correlated, and hence, yield a large probability for $H_i = H_j$. The path loss model described in (3.5) was used for simulation. A high sea state with a wave height between 4.27 m and 6.10 m [47] was used to evaluate the simulation results. Random values of wave height were generated. Therefore, the SNR value for each ship changed continuously.

As argued in section 6.1, there is no publicly known cognitive routing protocol for a CR-SDMN that combines a cognitive capability with a routing technique by using the SDN approach. Therefore, we chose to compare this proposed scheme with a hierarchical software-defined VANET (HSDV) [100] and an expected path duration maximized routing (EPDM-R) [29] algorithm. These protocols were actually proposed for vehicular networks as mentioned in chapters 2 and 5. Because two networks are concerned with topological constraints, and a ship at sea is analogous to a vehicle in traffic, we evaluated these protocols in a marine environment just for the sake of comparison. Furthermore, in order to make HSDV a cognitive routing scheme, we simulated it in combination with the spectrum sensing

scheme proposed by Tang *et al.* [43] for cognitive maritime networks and refer to it as the reference scheme with SDN. To evaluate the impact of utilizing controllers in this proposed scheme, we made another comparison with an EPDM-R that does not consider SDN, and we refer to it as the reference scheme without SDN. This scheme is similar to AODV, which selects the best route from source to destination from among all attainable paths. Three metrics were used to evaluate the performance of this proposed scheme: (a) end-to-end delay, (b) packet delivery ratio, and (c) routing overhead ratio.

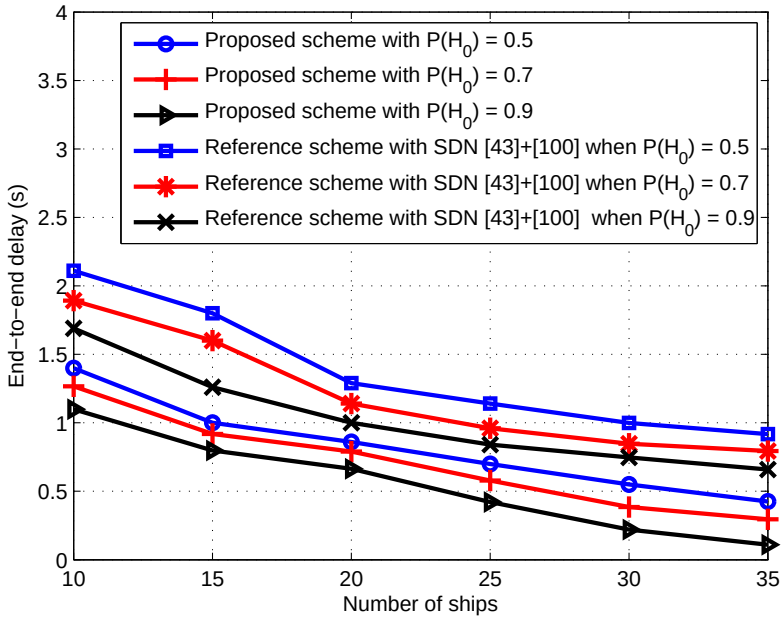


Figure 6.4: Performance comparison between two SDN-based schemes in terms of end-to-end delay.

Figures 6.4 and 6.5 show the performance of end-to-end delay as a function of the number of ships, with different probabilities of the PU being idle as a parameter. These figures show a comparison of this proposed scheme with the SDN-based and non–SDN-based reference schemes, respectively. With an increasing number of ships in the network, the delay decreases. The pattern is the same for all the schemes, i.e. when increasing the

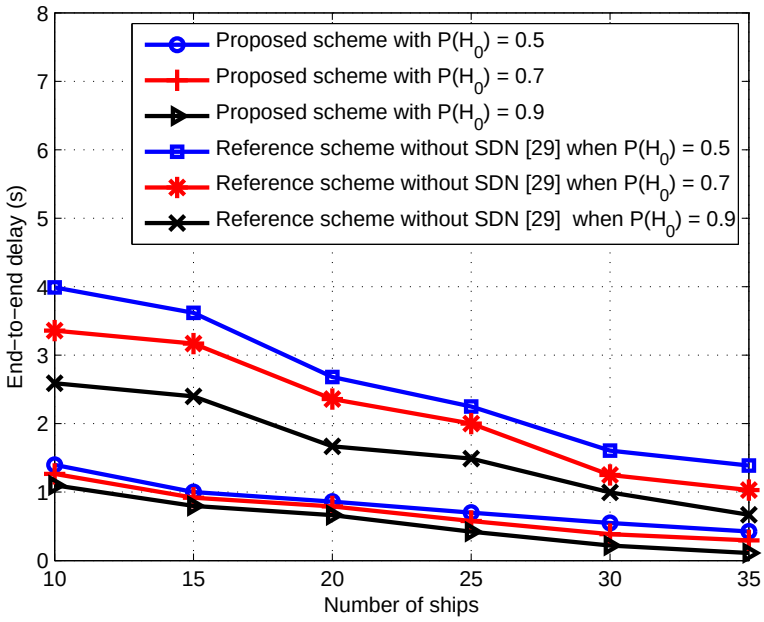


Figure 6.5: Performance comparison between SDN and non-SDN schemes in terms of end-to-end delay.

number of ships and increasing the probability of the PU being idle, delay decreases. This is because connectivity in the network increases with an increase in the number of ships, and in the latter case, the high probability increases the chances of more idle channels in the network. When the network is sparse (between 10 and 15 nodes), the delay is high for all the schemes. This is because the querying node does not find any other node to make a stable link (under sparse network conditions), and therefore incurs a large delay. However, in this proposed scheme, the CHs allow a querying node to make a stable link by connecting with a gateway that serves as a relay node, even under sparse network conditions. Hence, selecting the CHs in the proposed scheme further reduces the delay. When these CHs know the route to the destination, they reply to the querying node with the updated route without communicating with the MC, and thereby reduce network delay. Hence, the target in this chapter is to maintain network stability by providing the best route between

source and destination. For that reason, this proposed scheme shows less delay, compared to both reference schemes. The reference scheme in Fig. 6.4 selects the next node based on distance only, whereas this proposed scheme calculates the link estimation time, which includes both the speed and direction of the ships. In the reference scheme of Fig. 6.5, each node selects its next relay node to form a stable link, hop-by-hop, which incurs a large delay in the network; in this proposed scheme, each querying node directly makes a connection with the controller (CH or via CH) to get a stable route. Both Fig. 6.4 and Fig. 6.5 show that decreasing the idle probability decreases network performance. This is from facing the difficulty in finding a common free channel when the idle probability of the PU decreases. Likewise chapters 2, 3, and 5, in comparison with other spectrum-sensing techniques, the BP algorithm in this proposed scheme outperforms the spectrum sensing approach of the reference schemes. The BP algorithm enhances the accuracy of hypotheses concerning spectrum availability, and therefore, the overall performance of this proposed scheme in terms of delay is better than the other two schemes.

Figures 6.6 and 6.7 show the performance of packet delivery ratio as a function of the number of ships, with different probabilities of the PU being idle as a parameter. The packet delivery ratio for both the proposed and reference schemes increases with an increasing number of ships in the network. The SDN approach improves network performance in terms of delivery ratio because of the logically centralized controller that dictates the behavior of the network. In the reference scheme without SDN, a querying node has to select the next node for every hop until it reaches the destination. By doing so, it may come across several fragile links due to the constant movement of the sea′s surface. Correspondingly, for every unstable link, the scheme needs to update all the nodes between source and destination as to the current network state. However, in this proposed scheme, the MC keeps a global view of the network, which means the MC manages all the information about

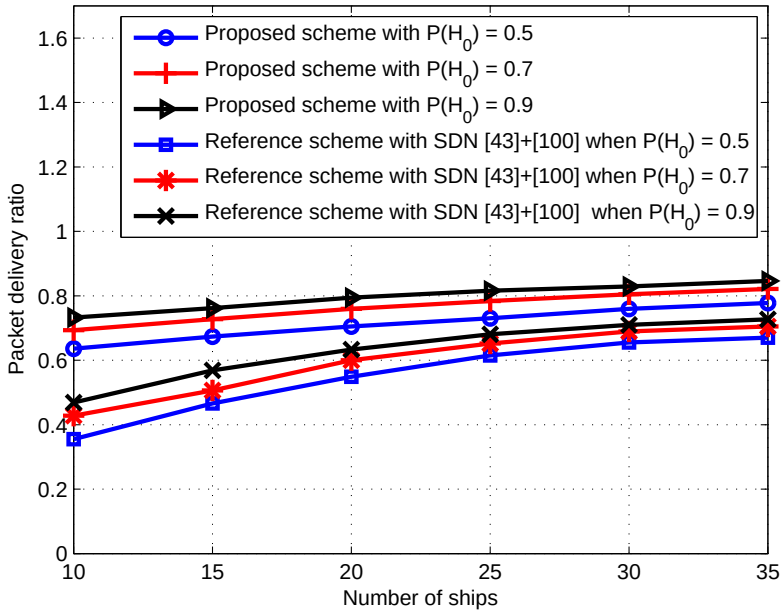


Figure 6.6: Performance comparison between two SDN-based schemes in terms of packet delivery ratio.

idle channels and relay nodes for each cluster in the network. Therefore, by calculating the path duration, the MC provides the best stable route between source and destination to each querying node. Furthermore, in any case of an unstable link due to the unavailability of any ship or channel, the querying node directly asks the MC for a route update without sending the packet back to the source node. Hence, this proposed scheme increases network stability by providing more-stable routes, which increases the packet delivery ratio. Fig. 6.6 shows that the proposed scheme in this chapter outperforms the reference scheme with SDN, even though both are SDN-based schemes. The reason is the difference in the selection of the route between source and destination. Selecting the nearest ship to the destination (based on distance) only makes more sporadic links, which decreases the successful delivery of packets. Fig. 6.6 and 6.7 also show that when increasing the idle probability of the PU, the packet delivery ratio increases for all the schemes. The reason is the same;

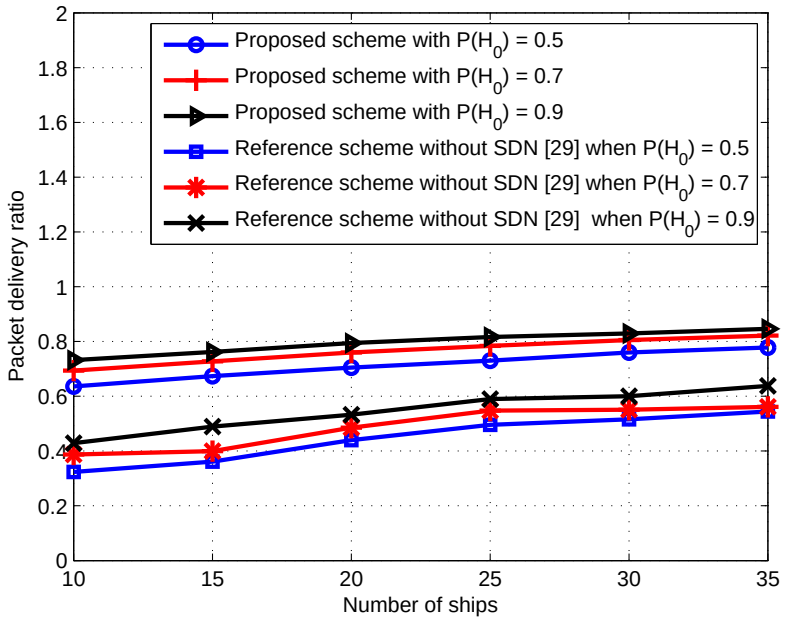


Figure 6.7: Performance comparison between SDN and non-SDN schemes in terms of packet delivery ratio.

the number of free channels increases with the high probability. When the idle probability is low, there are fewer chances for ships to make a stable link, because they do not find consensus on a common free channel. A low probability means that a ship may not select a CH because it does not find a common channel between the two, thereby decreasing the chance for CM-to-CH communication. As a result, the performance degrades when the idle probability of the PU decreases.

Figures 6.8 and 6.9 show the performance of routing overhead ratio as a function of the number of ships, with different probabilities of the PU being idle as a parameter. From the figures, we can see that the routing overhead ratio increases with an increase in the number of ships and with a decrease in idle probability under the proposed and reference schemes. However, the overhead ratio of SDN-based schemes shows better performance than the non–SDN-based approach. This is due to the logically centralized controller,

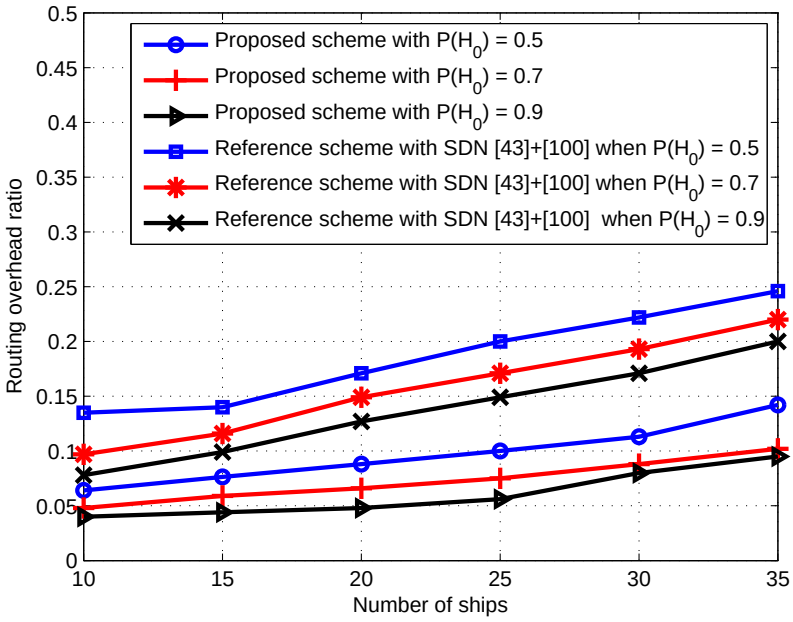


Figure 6.8: Performance comparison between two SDN-based schemes in terms of routing overhead ratio.

which reduces the number of control messages in the network. Each querying node in the SDN-based scheme communicates with the controller (either MC or LC) whenever it encounters a packet mismatch or it requires any route update. However, in the non–SDN-based approach, the querying node sends beacon messages to all the neighboring nodes for each update on the current network state. Consequently, with a higher number of ships, the message update rate is also high. The proposed scheme in this chapter outperforms both reference schemes. The reason for the better performance is the main controller, which keeps a global record of updated information due to the cooperation among the CHs with the help of ASVs. Moreover, selecting the most stable route between source and destination at the controllers by maximizing the path duration reduces overall network overhead. On the other hand, the distance-based selection in the reference scheme with SDN shows performance degradation in terms of overhead ratio, as stability is not assured. Fig. 6.8 and 6.9 also

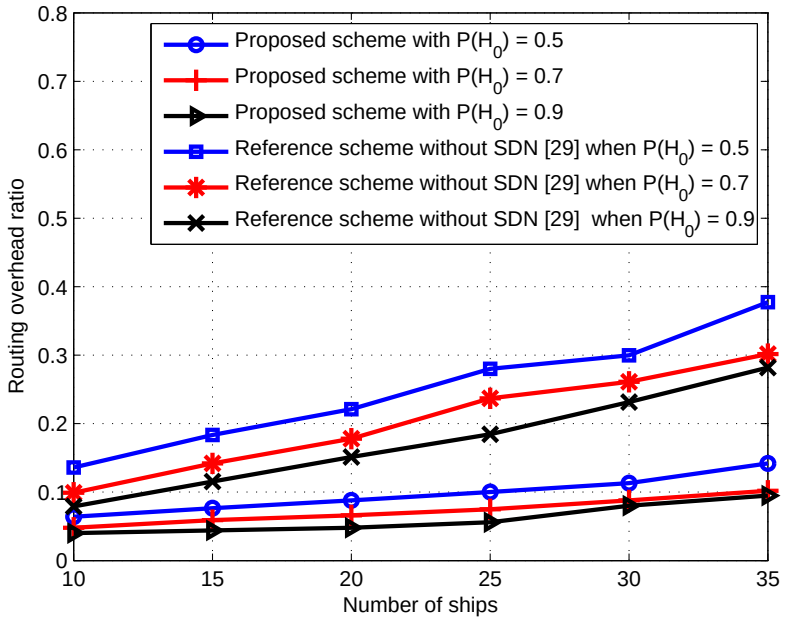


Figure 6.9: Performance comparison between SDN and non-SDN schemes in terms of routing overhead ratio.

show that decreasing the idle probability of the PU increases the overhead. This means that ships have fewer chances of finding a common idle channel, and thus, the message exchange rate among ships increases in order to find an idle channel. A complete analysis of the simulation results in this chapter show that SDN-based schemes outperform the non–SDN-based scheme, and this proposed scheme outperforms the two reference schemes. Also, decreasing the idle probability of the PU decreases network performance.

6.4 Chapter summary

In this chapter, a novel routing protocol for cognitive radio software-defined maritime networks is proposed. The idea of combining a cognitive capability with a routing scheme in software-defined maritime networks makes this protocol unique. The protocol has two phases: beaconing and route estimation. A main controller is responsible for network man-

agement, while CHs, serving as local controllers, reduce the number of control messages and any network delay. The ships are moving in clusters at different positions from the MC. Therefore, CHs that are close to the shore make a direct connection with the MC, while the CHs far out at sea consider ASVs as gateways to relay the data to and from the MC. ASVs are moving on fixed routes and are also used to relay data through CH-to-CH communication. The controllers are responsible for providing a stable route between source and destination for any querying source. A link is formed between two nodes if they have consensus on a common idle channel. A belief propagation algorithm is used to collect the local sensing results of each ship in order to make a global decision. The results in this chapter show better performance in end-to-end delay, packet delivery ratio, and routing overhead ratio for software-defined cognitive maritime networks.

Chapter 7

Software-Defined Cognitive Underwater Acoustic Networks

7.1 Introduction

Existing underwater networks are composed of thousands of nodes that are deployed to collect data in an area of interest in the ocean, thereby satisfying the requirements of a single application. Along with previous all issues discussed in chapter 4, another issue in these networks is that due to application constraints and vendor dependency, it is difficult to use these nodes for other services in the same area [93]. To overcome the shortcomings with existing architectures in underwater networks, this chapter intends to apply SDN in this domain. SDN technology offers the flexibility to adapt and satisfy different applications. As mentioned in chapter 4, several routing protocols have been proposed for underwater networks, but for cognitive underwater networks, the number of protocols that consider a cognitive capability with a routing technique is limited. The channel-aware routing protocol (CARP) [120] is a robust relay-selection mechanism to achieve high-throughput efficiency.

Yoon *et al.* [121] proposed an autonomous underwater vehicle (AUV)-aided underwater routing protocol (AURP) to maximize the data delivery ratio and minimize the energy consumption of underwater sensor nodes. This was the first protocol to employ multiple AUVs as relay nodes in a multi-hop underwater acoustic sensor network. Coutinho *et al.* [122] proposed a geographic and opportunistic routing protocol with depth adjustment-based topology control for communication recovery (abbreviated as GEDAR) to improve the data packet delivery ratio in mobile underwater sensor networks. Ilyas *et al.* [123] proposed an AUV-aided efficient data-gathering (AEDG) routing protocol for reliable data delivery in underwater sensor networks. Rani and Talwar [124] proposed an energy-efficient chain-based routing protocol for data gathering in underwater sensor networks. AUV-aided routing method integrated path planning (AA-RP) [125] integrated the AUVs dynamic path planning algorithms into the routing protocol.

None of these routing protocols for underwater sensor networks considered spectrum scarcity issues caused by limited communications frequencies. Proposing a cognitive routing protocol that takes the spectrum scarcity issue into account is essential in order to meet the increasing demands of underwater acoustic users. Luo *et al.* [126] proposed a novel medium access control (MAC) protocol, called dynamic control channel MAC (DCC-MAC), by investigating the congestion of control channel in a UCAN. Li *et al.* [127] proposed a cognitive acoustic transmission scheme, called dolphin-aware data transmission (DAD-Tx) to achieve the optimal end-to-end throughput with dolphin awareness. Similarly, research in software-defined underwater networks is still very limited. SoftWater [128] was first introduced to facilitate such developments and to support a variety of applications for next-generation underwater sensor networks. A software-defined network-based solution [93] was proposed to build an architecture for underwater networks in big data, which includes design of both the data plane and control plane. A new high data rate software-defined underwater

acoustic networking platform, SEANet G2 (second generation) [129], was proposed to provide several benefits over existing underwater acoustic platforms. Lal *et al.* [92] discussed and reviewed the state-of-the-art security threats for underwater networks along with their existing solutions. The study presented future solutions based on software-defined cognitive networking with the support for cross-layering communications and context-aware networking. Consequently, combining cognitive principles with routing schemes to design an algorithm for cognitive acoustic software-defined underwater networks has not yet been considered. This is the first work implementing a cognitive routing protocol in an software-defined underwater network (SDUN) that simultaneously considers spectrum sensing and routing for underwater communications.

The main objective of this chapter is to combine a cognitive capability with a routing technique in underwater networks by using the SDN approach. This chapter intends to overcome the problems of spectrum scarcity and high latency in UCANs. The goal here is to select the best route between source and destination that maximizes the capacity and minimizes the duration among all the paths. Likewise chapter 4, spectrum sensing is done with an OFDM-based energy detection scheme. The SDN controllers programmatically configure the traffic and have a global view of the network. This proposed scheme has a single MC and several LCs. LCs are mobile AUVs that have a localized view of the network. Sensor nodes send requests to LCs querying them for a route to the target node. The LC quickly responds to the request if it has a route to the destination; otherwise, it forwards the request to the MC.

The remainder of the chapter is organized as follows. In Section 7.2, a cognitive routing protocol for software-defined underwater acoustic networks is proposed. Section 7.3 discusses simulation performance results, while Section 7.4 concludes the chapter.

7.2 Proposed cognitive acoustic software-defined underwater network

A cognitive routing protocol for software-defined underwater acoustic networks is proposed in this chapter. The objective of this novel routing protocol is to overcome major issues in existing underwater communications that lead to network deterioration. This work combines a cognitive capability with a routing technique in underwater networks by using SDN as a new candidate to improve network performance and communications reliability. Taking advantage of SDN, we propose that the sensor nodes within the considered network be used for various services in the same area. This means that the sensor nodes working for one application collect information from their surroundings and send the gathered data to the controller. This logically centralized controller then performs data scheduling and network management to collect information of interest for any other application in order to take full advantage of the whole network. The aim of this chapter is to find a stable route between source and destination by jointly selecting the channel and relay node in an efficient and reliable manner. A cognitive acoustic software-defined underwater network (CA-SDUN) is shown in Fig. 7.1, where a source node in the deep ocean is looking for a stable route to a destination far away from it at a different depth in the ocean. The CA-SDUN considers C different communicating nodes. A surface buoy serving as a main controller keeps global updated information on the network. The mobile AUVs (i.e., LCs) improve network reliability by sharing the burden of the single main controller. LCs move on fixed trajectories where the track is maintained by the MC. The sensor nodes, G, within transmission range of the LCs$'$ track, serve as gateways between conventional sensor nodes, N, and the AUVs, and send information to all neighboring nodes as an extended beacon message. The nodes receiving the messages keep a record of these gateways in their flow ta-

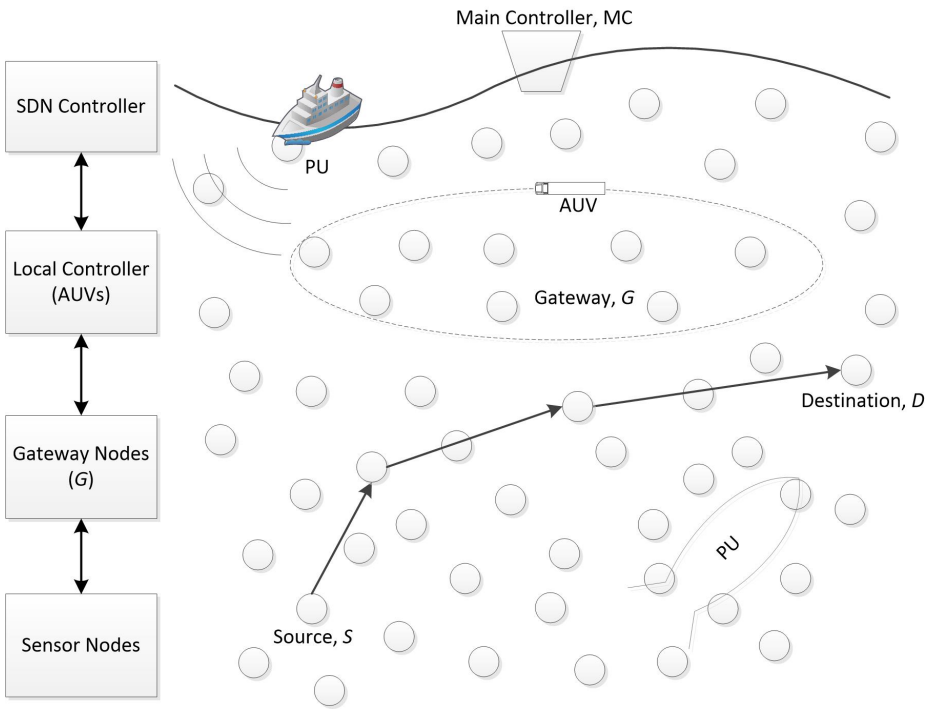


Figure 7.1: Cognitive acoustic software-defined underwater network (CA-SDUN).

bles. This is a four-layered hierarchical network scheme where the first two layers (MC and LCs) communicate directly with each other while gateways (the third layer) are used between sensor nodes (the fourth layer) and the AUVs, as shown in Fig. 7.1. These gateways collect data from all neighboring nodes and store this information until passing it over to the LCs. The double-layering of controllers (MC and LCs) improves network performance in terms of delay and overhead. Both natural acoustic systems (e.g., marine mammals) and artificial acoustic systems (e.g., sonar systems) play the role of PUs, as shown in Fig. 7.1. All sensor nodes periodically update their current network state with each other and send the gathered information to LCs (either directly or via gateways). All LCs share their localized view of the network with the MC, such that the MC establishes a global network view.

Likewise the proposed protocols in chapters 5 and 6, this protocol also has two phases: beaconing and route estimation. The beaconing phase establishes the global and localized network states for the MC and LCs, respectively, and updates all the sensor nodes with the current network state. In the route estimation phase, a querying node sends a route request message to an LC. On receiving the message, the LC checks its flow table to determine if it has an updated route to the destination. It quickly responds to the source node without contacting the MC if it finds the updated route in its flow table. In the following, we will discuss each phase in depth.

1. **Beaconing phase:** In the beaconing phase, all sensor nodes (either gateways or conventional nodes) send a beacon message to their neighbors. The beacon message includes node ID, depth, channel state, and speed. Channel state is the presence or absence of the PU, which is the same as explained in the subsection 4.2.1. The MC sends a request message to the LCs in order to maintain the global network state. Each LC forwards this message to all the nodes within transmission range. By doing so, gateway nodes exchange the gathered data with the LCs, which forward it to the MC. The gateway nodes identify themselves as a gateway (an extra entity) in the beacon message. At the conclusion of this phase, all the communicating nodes in the network are aware of the updated network state. In this way, any querying node, whenever it comes across link fragility, can ask the controller for an updated stable route to a destination without sending the packet back to the source node.

2. **Route estimation phase:** When a source node wants to communicate with the destination node, it sends a request message to the controller. The foremost part of this cognitive routing scheme that makes it efficient is the estimation of path duration between source and destination. This is a challenging task for any source node in an

underwater environment when one kind of PU includes marine mammals. To make it possible, we apply the SDN technique so that the controllers are responsible for providing the best stable route between source and destination by jointly selecting both channel and relay. We all know that the unpredicted movement of marine mammals makes the underwater environment more challenging, which results in several fragile links. For that reason, the two layers of controllers help the sensor nodes with the provision of stable links by keeping an updated network state. There are two possibilities for the source node: either it is outside the transmission range of an LC, or it is within transmission range of an LC.

Case 1: *Source outside transmission range* The source node needs to find the best relay node to reach any gateway when it is outside the transmission range of any LC. The source sends a beacon message to all neighboring nodes and calculates the transmission delay for each node within transmission range. The source then selects the relay node that has the minimum transmission delay from among all the neighboring nodes. As in chapter 4, the transmission delay (s) is calculated using (4.9). Here, $\widehat{N}_{ij}^{Hop} = max\left(\frac{D_{i,MC}}{<D_{ij}>_{i,MC}}, 1\right)$, in which $< D_{ij} >_{i,MC}$ is the projection of distance D_{ij} on the line connecting the source to the MC. One might think the MC is not the target of the source if an LC finds a route to the destination in its flow table. The reason for calculating this projection with respect to the MC is to minimize the transmission delay in reaching a controller in order to improve overall network performance. This will also reduce the number of hops by selecting the nodes farthest from the source/querying node. Another reason is the calculation of depth; it is more reasonable to identify surface depth than to estimate the depth of a moving AUV.

Among all the neighboring sensor nodes within transmission range of the source node, the source selects the one that has the minimum TD to reach any gateway. Therefore,

the best relay node is calculated as:

$$min(TD_1, TD_2, ..., TD_N) \tag{7.1}$$

where N is the total number of neighboring nodes within transmission range of the source node. In so doing, the source node selects the relay node hop-by-hop, and finally reaches the gateway. As this is a cognitive routing scheme, several gateways help the network to make stable links, thereby reducing the delay. Two nodes can only communicate if they have consensus about a common idle channel. Therefore, the gateway set increases the chances that there is a single gateway available to make a stable link. The gateway stores the information until it establishes a link with the AUV. If a relay node finds itself within transmission range of the AUV, it will send the packet directly to the AUV. Once a link is established with an LC, the LC checks its flow table for a route to the destination. If the LC does not find a route to the destination, it sends the request packet to the MC to find the best stable route to the destination.

Case 2: *Source within transmission range* When a source is within transmission range of an LC, it directly sends a request packet to the LC; otherwise, it finds a gateway from set G. The LC checks in its flow table for a route to the destination, and sends a reply message if it has the best route to the destination. If it does not find a match, it forwards the request packet to the MC. Once the message reaches the controller, the LC/MC estimates the best stable route to the destination in the following manner. Any controller first calculates the path duration (s) of all paths P between source and destination as follows:

$$PD_p = min(LDP_{1,p}, LDP_{2,p}, ..., LDP_{TH,p}) \tag{7.2}$$

where $p = 1, ..., P$, TH is the total number of hops making up each path between

source and destination, and $LDP_{i,p}$ (link duration prediction) (s) is calculated as:

$$LDP_{ij}^{ch} = \frac{L_s}{r_{ij}^{ch}} + GD_{ij} + ENC \tag{7.3}$$

where ENC is the expected node connectivity, which can be measured from all the beacon messages a node receives from its neighboring nodes within transmission range in time t, i.e. $\frac{1}{hello\ messages/t}$. This connectivity parameter helps the network to avoid sparse conditions for both channel and relay selection. Finally, the controller finds the best route, R, to the destination:

$$R = min(PD_p) \tag{7.4}$$

The source node, after receiving the best route, starts transmitting data. As this is a cognitive routing scheme, minimizing the path duration enhances the stability of the network that has a high data rate with low delay. This is because the unique challenges of underwater environment along with mobile PUs increase the chances of link fragility. Therefore, selecting the route with high data rate and low delay sustains stability in underwater networks. If any intermediate node fails to sustain stability, it repeats the above procedure to reach a nearby LC without sending the request packet back to the source node. Consequently, the SDN approach reduces delay by reducing the number of control messages.

The summary of the proposed algorithm is explained by considering an example scenario, as shown in Fig. 7.1. Assume that the MC and all LCs have the global and the localized view of the network, respectively. Source S is looking for a stable route to reach destination D. The source reaches gateway G by making hop-to-hop links using (4.9). G forwards the request packet to an LC. The LC checks its flow table and does not find a match. It forwards the packet to the MC, which calculates a stable route using (7.3). The MC sends this packet to the LC, which sends it back to the source node. The source finally

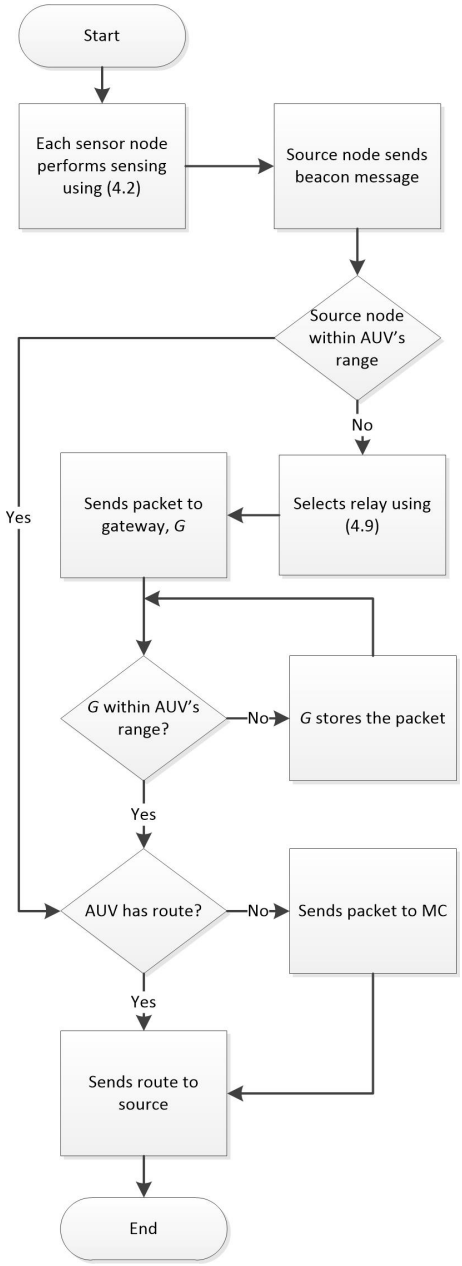


Figure 7.2: A flowchart representing the CA-SDUN protocol.

forwards the data packet to the destination via the prescribed route. The flow chart of the complete algorithm is shown in Fig. 7.2.

7.3 Simulation results and discussion

The performance of CA-SDUN is evaluated in the same simulators used in chapter 4 with almost the same parameter settings. Therefore, we skip to mention those parameters again here. In this scheme, the randomly placed sensor nodes are distributed in a target area of 700 m $\times$ 700 m $\times$ 700 m, each having a transmission range of 100 m. The number of PUs moving randomly in the network was two. The number of AUVs used was two, each moving at a speed of 1.5 m/s and having a transmission range of 300 m. There was one MC placed at the surface of the ocean. The number of sensor nodes varied from 10 to 30. Due to the same reason of not having publicly known cognitive routing protocol as mentioned in previous chapters, we chose to compare CA-SDUN with two reference schemes (one previous scheme [58] as mentioned in chapter 4 and another AA-RP [125]), each again in combination with an energy detector-based spectrum sensing scheme [79] for underwater cognitive sensor networks. For simplicity, we denote these schemes as Cog-AA-RP and Cog-DVRP. AA-RP considers AUVs as mobile sinks that collect data from sensor nodes and forward the collected data to the surface. A gateway node (GN) is an agent of an AUV which communicates with the AUV when ordinary sensor nodes fail to make a connection. The GN stores information until it forwards it to the AUV. Cog-AA-RP modifies the AA-RP protocol such that each sensor node (including the GN and the AUV) first senses the spectrum and exchanges the local sensing results to find common idle channels. Finally, it implements the key idea of AA-RP to collect data to forward to the surface station.

Figure 7.3 shows the performance of average delay as a function of the number of sensor nodes with the number of channels as a parameter. The average delay decreases with an increase in the number of sensor nodes. The pattern is the same for the three schemes, i.e., when increasing the number of sensor nodes and increasing the number of channels,

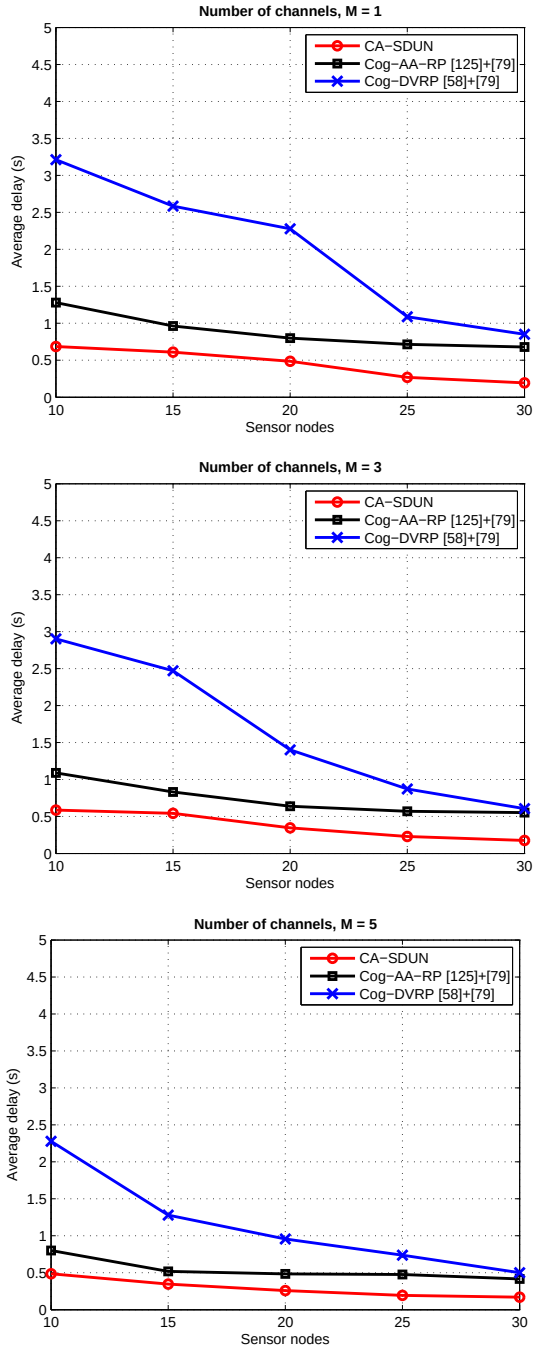


Figure 7.3: Performance comparison between CA-SDUN, Cog-AA-RP, and Cog-DVRP for average delay as a function of the number of sensor nodes with different numbers of channels, M. (a) average delay when $M = 1$; (b) average delay when $M = 3$; and (c) average delay when $M = 5$.

delay decreases. This is because the connectivity in the network increases with an increase in sensor nodes, and in the latter case, the large number of channels in the network increases the chances for the sensor nodes to have even more common idle subcarriers. With fewer sensor nodes, the delay is high for all the schemes because a packet usually has to wait longer than normal to find the next hop node. Moreover, finding a common idle channel in cognitive communications scenarios is another reason for packet delay. As our goal is to maintain network stability by providing the best route between source and destination, we therefore applied the SDN approach where controllers know the route to the destination by keeping an updated network topology. In CA-SDUN, considering that the AUVs on fixed trajectories serve as LCs further reduces the delay. When these LCs know the route to the destination, they reply to the gateway/querying node with the updated route without communicating with the MC, and thereby reduce network delay. On the other hand, AUVs in Cog-AA-RP select nodes based on the distance and neighbor information of the first-hop node after finding a common idle channel between two communicating nodes. Hence, CA-SDUN outperforms Cog-AA-RP because it allows each querying node to directly make a connection with the controller to get a stable route. Also, both CA-SDUN and Cog-AA-RP outperform Cog-DVRP. This is because Cog-DVRP restricts the neighboring set for the querying node. The querying node is bound to select a relay node within the flooding zone. As this is a cognitive routing scheme, the elementary step of selecting a common idle channel between two communicating nodes further degrades the performance of this reference scheme. As a result, finding a relay node within the flooding zone decreases network performance by reducing the number of sensor nodes.

Figure 7.4 shows the performance of packet delivery ratio as a function of the number of sensor nodes with the number of channels as a parameter. The delivery ratio increases with an increase in the number of sensor nodes. The SDN approach in CA-SDUN

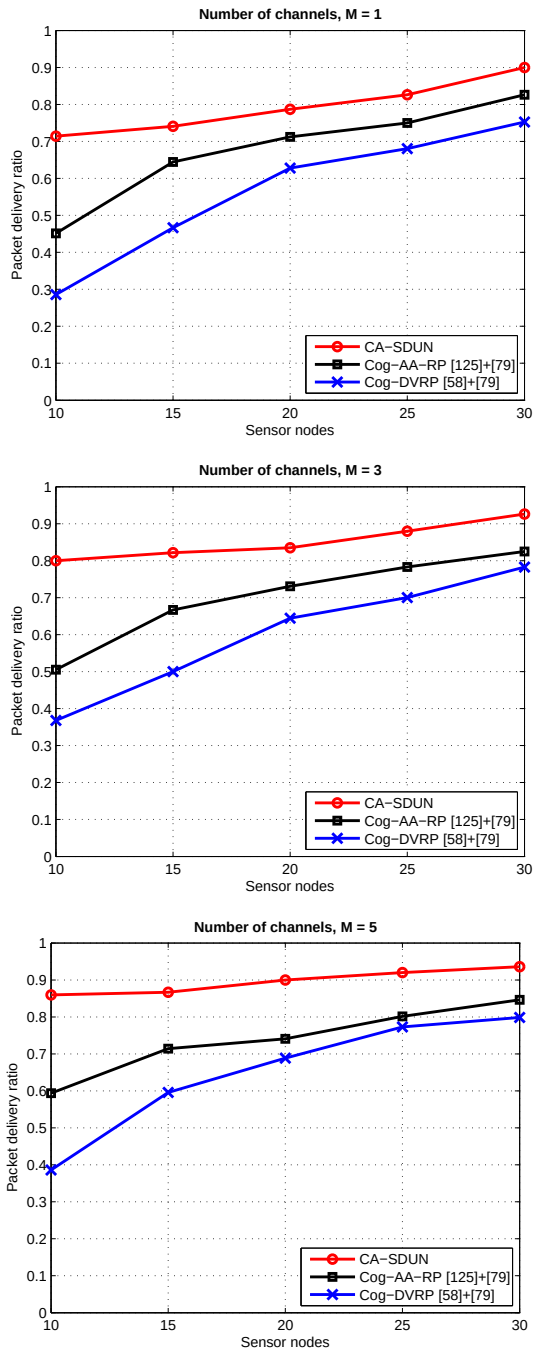


Figure 7.4: Performance comparison between CA-SDUN, Cog-AA-RP, and Cog-DVRP for the packet delivery ratio as a function of the number of sensor nodes with different numbers of channels, M. (a) packet delivery ratio when $M = 1$; (b) packet delivery ratio when $M = 3$; and (c) packet delivery ratio when $M = 5$.

improves network performance in terms of delivery ratio because of the logically centralized controller that dictates the behavior of the network. In Cog-DVRP, a querying node has to select the next node for every hop until it reaches the surface of the ocean. By doing so, it may come across several fragile links due to greater delay, resulting in link failures and a low packet delivery ratio. However, Cog-AA-RP outperforms Cog-DVRP because the AUV is responsible for forwarding data from sensor nodes to the surface of the ocean. Nevertheless, the selection of a GN by the AUV with the restriction of a common idle channel lowers the delivery ratio in comparison with CA-SDUN. In this proposed scheme, the MC keeps the global view of the network, which means the MC manages all the information about idle channels and relay nodes. Therefore, by calculating the path duration, the MC provides the best stable route between source and destination to each querying node. In the cognitive underwater environment, in addition to underwater environmental challenges, another factor that affects the packet delivery ratio is the selection of a common idle channel. We can see from Fig. 7.4 that increasing the number of channels increases the chance for the sensor nodes to have even more common idle subcarriers. However, for CA-SDUN, the packet delivery ratio is higher for different numbers of channels in comparison with the other two reference schemes. The reason is the selection of the relay node based on minimum transmission delay. When there is only a single channel in the network, there is a smaller number of idle subcarriers; hence, CA users face difficulty in accessing subcarriers free from a PU. Increasing the number of channels allows CA users to access the common idle sub-bands, and increases the chances for more sensor nodes to participate in the network. Hence, in this regard, the delivery ratio under CA-SDUN is the highest, compared to other scenarios, when the number of channels is $M = 5$, as shown in Fig. 7.4c.

Figure 7.5 shows the overhead ratio of CA-SDUN, Cog-AA-RP, and Cog-DVRP as a function of the number of sensor nodes, with the number of channels as a parameter.

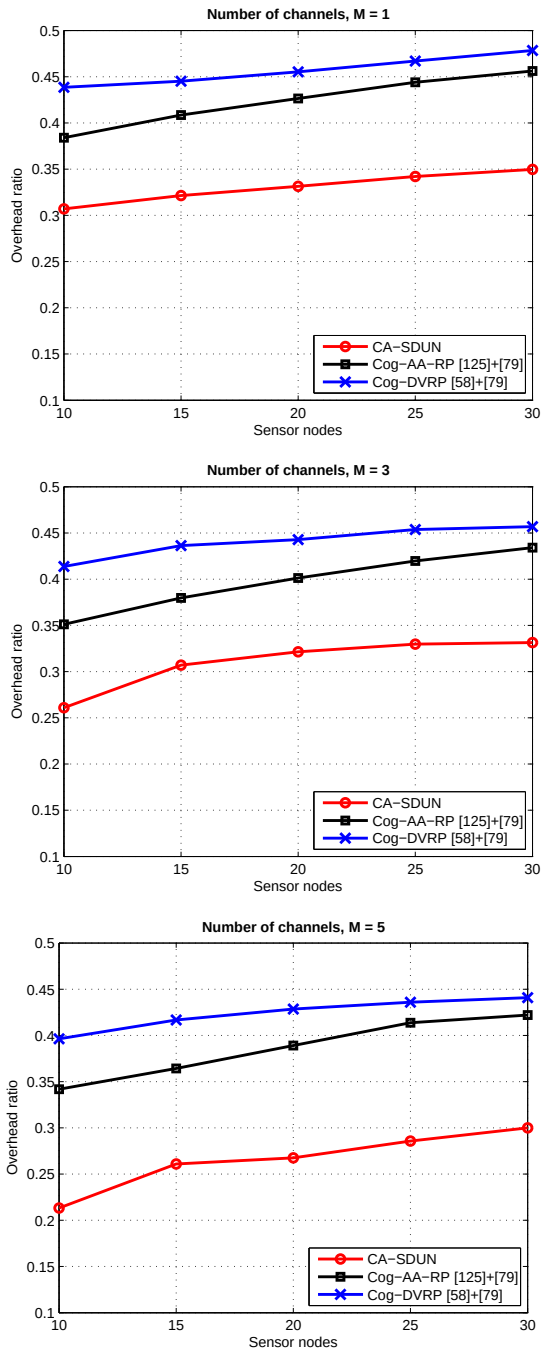


Figure 7.5: Performance comparison between CA-SDUN, Cog-AA-RP, and Cog-DVRP for overhead ratio as a function of the number of sensor nodes with different numbers of channels, M. (a) overhead ratio when $M = 1$; (b) overhead ratio when $M = 3$; and (c) overhead ratio when $M = 5$.

The routing overhead for the three schemes increases with an increasing number of sensor nodes in the network. We observed similarity in all the schemes in terms of an increase in overhead ratio when the number of sensor nodes increased and the number of channels decreased–the more sensor nodes, the higher the message update rate. However, CA-SDUN outperforms both reference schemes. This is because of the centralized controller, which reduces the number of control messages in the network. Each querying/gateway node in CA-SDUN communicates with the LCs whenever it encounters a packet mismatch or it requires a route update. When these LCs know the route to the destination, they reply to the querying nodes with the updated route without communicating with the MC, and thereby reduce the message rate. Moreover, in any case of an unstable link due to the unavailability of any sensor node or channel, the querying node directly asks the LC for a route update without sending the packet back to the source node. However, in the reference schemes, nodes send beacon messages to all neighboring nodes for each update on the network state. The overhead ratio for both Cog-AA-RP and Cog-DVRP is higher than for CA-SDUN. In Cog-AA-RP, the AUV sends hello messages to all the first-hop neighboring nodes to choose GNs in a timely manner, and these GNs exchange messages with sensor nodes to collect data; hence, a large overhead is incurred. On the other hand, in Cog-DVRP, calculating the flooding zone further reduces the chances of successful packet delivery. This is because sensor nodes may not find a common idle channel for communications, which therefore increases the overhead ratio. Fig. 7.5 also shows that increasing the number of channels increases the free subcarriers in the network, and thereby decreases overhead by providing a larger number of unused subcarriers to all types of sensor node for stable communications. A complete analysis of the simulation results in this chapter shows that the SDN-based scheme outperforms non–SDN-based schemes, and using AUVs in the network enhances network performance.

7.4 Chapter summary

In this chapter, a novel routing protocol for cognitive acoustic software-defined underwater networks is proposed. The idea of combining a cognitive capability with a routing scheme in software-defined underwater networks makes this protocol unique. The protocol has two phases: beaconing and route estimation. A main controller is responsible for network management, while AUVs serving as local controllers move on fixed trajectories to reduce the number of control messages and any network delay. The controllers are responsible for providing a stable route between source and destination for the querying node. A link is formed between two nodes if they have a consensus about a common idle channel, and a link with the minimum duration is selected to make a stable route. Both natural acoustic systems and artificial acoustic systems are considered to be PUs in this scheme. Therefore, spectrum sensing is performed with an OFDM-based energy detection scheme. The results in this chapter show better performance for average delay, packet delivery ratio, and routing overhead ratio. For sensing channels and then selecting relay, a large amount of energy is required in the proposed scheme. Therefore, it is an urgent problem to consider a good trade-off among energy consumption, overhead, and delay for cognitive routing schemes based on traffic and energy balancing. Also, energy harvesting techniques, such as harvesting energy from acoustic links to recharge sensors/AUV batteries, should be considered to prolong the network lifetime. We have left these research issues for future work.

Chapter 8

Software-Defined Cognitive Networks with Fog Computing and Network Function Virtualization

8.1 Introduction

Smart city is an up-and-coming architecture that include various kinds of systems that provide an improved quality of life to their citizens, with a variety of applications for entertainment, health care, education, and so on [130, 131]. In order to facilitate various applications, ranging from safety to entertainment-related information for passengers and to fulfill all the expectations in providing services from each of these applications, we introduce two integrated cognitive architectures in this chapter. We citizens are actually exposed to a plethora of mobile applications for different networks. These networks can be terrestrial, maritime, or hybrid; the combination of the two. This increase in the number of smart devices causes difficulty in maintaining stable networking and in meeting the increasing de-

mands of different users. Centralized cloud computing has been used as a straightforward alternative to implementing complicated services; however, due to latency constraints in different networks, cloud computing is not a good remedy for these issues [132]. Fog computing (FC) is a technology that brings services nearer to the end user, thereby improving end-to-end latency. Due to the highly dynamic nature of vehicles on roads and ships in the sea, another issue is establishing a stable route to provide diversified services for different network applications. Software-defined networking (SDN) and network function virtualization (NFV), two emerging notions that are gaining popularity in both academia and industry, have inspired a good way to solve this problem [133]. Moreover, dedicated spectrum for automobile and maritime communications systems have been found insufficient to deal with the developing requirements of applications [6, 7]. Cognitive radio was announced as a promising technology to resolve spectrum scarcity issues in different networks. Consequently, to maintain stable networking and meet the increasing demands of mobile data traffic, network engineers are required to provide an effective solution to improve users′ experiences. This means that citizens need an all-in-one framework to meet their growing needs in a more effective and efficient way.

To cope with the inevitable increase in data traffic, integration of SDN and NFV seems to be a viable solution to launching and managing virtual networks (VNs) on demand at greater speed, respectively. NFV is basically a transition from proprietary hardware-based solutions to multi-vendor open solutions. NFV is like a soft appliance that can be installed on demand, whereas SDN is smart plumbing that can be changed on command. The integration reduces provisioning time from months to minutes, reduces costs, improves service-request response times, reacts faster to changing services (allowing right-sized deployments to customers), and offers competitive services. Due to integration, the changing needs of virtual network function (VNFs) are now automatically followed by network con-

figurations, and an authorized person is able to track the owner of a service and the reasons why these certain configurations are required. A VNF is the virtualization of a certain NF that should operate independently. NFs are actually services that are deployed by NFV. SDN is a critical component in the majority of NFV deployments. NFV offers silo-free services (i.e., a common-layer platform with its compute, storage, and network resources) where there is no duplication for each service. The infrastructure supports NFs across many geographic locations. Both NFV and SDN are complementary technologies that simplify network management and that can be applied to different network types. NFV can use SDN as part of service function chaining (SFC), and SDN can provide connectivity between VNFs [134, 135].

The main objective of this chapter is to apply the idea of integration in cognitive networks to find a stable route from sources to destinations for different applications. An integrated cognitive vehicular network and an integrated cognitive coastal city are introduced in this chapter. The coastal city combines vehicular and maritime networks to find a stable route from source to destination for hybrid communications. To the best of our knowledge, this is the first work that considers routing service in cognitive networks with the integration of SDN, NFV, and FC. We integrate SDN, NFV, and FC to reduce complexities in the existing infrastructure. These complexities have high (unpredictable) latency and put high pressure on bandwidth due to explosive increases in data traffic, intermittent connectivity in vehicular and marine networks, and inconvenience with applications (that is, no exchange of information among applications). Because an NFV infrastructure supports network functions (network services deployed as virtual functions) across many geographic locations, we are therefore taking advantage of this notion and implement it in a combination of vehicular and maritime networks in a coastal city. A common network with different city applications is virtualized by a hypervisor into several virtual networks to

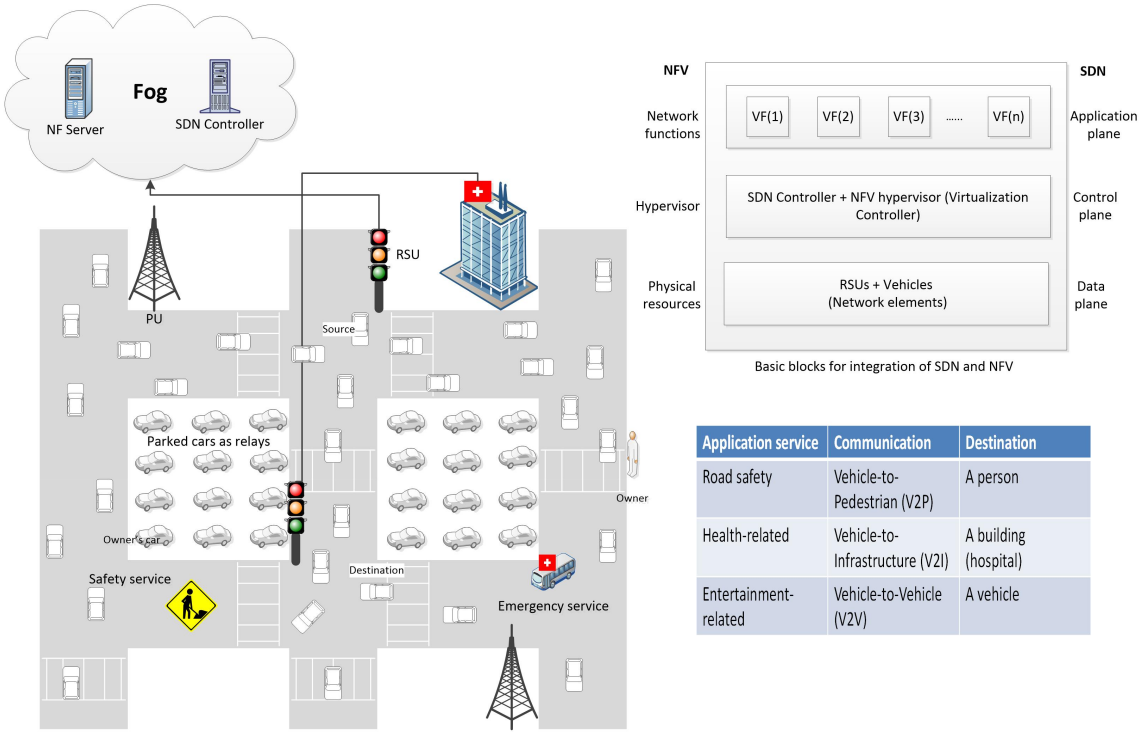
meet the demands of each application service. The hypervisor is a virtualization controller that allocates and manages the resources (forwarding tables in this chapter) over the fog cloud, and it launches VNFs dynamically. This means that a large city network is divided into smaller independent networks.

The remainder of the chapter is organized as follows. In Section 8.2, an integrated cognitive vehicular network and an integrated cognitive hybrid network are proposed. Section 8.3 discusses simulation performance results, while Section 8.4 concludes the chapter.

8.2 Proposed integrated cognitive networks

8.2.1 An integrated cognitive vehicular communications for smart cities

We open a new door for routing in cognitive vehicular networks by integrating SDN, NFV, and FC. We are taking the advantages from these three technologies to make the system flexible, faster (speedy), efficient, and reliable. The role of NFV is to quickly deploy and develop new applications and services according to users′ demands. SDN enables networking among different VNs by managing and controlling them. Fog computing reduces latency by bringing the cloud down near end users. This subsection focuses on establishing different routes for different applications using this integration in a cognitive vehicular network. Whenever a new application′s demand arrives, the fog cloud runs NFV and virtualizes the network according to the demands of each application. NFV checks the resources in its compute, network, and storage pools. If it has enough resources, it will launch a VNF for that demand. In a similar way, based on different demands, NFV launches several VNFs. The application owner sends a request message to NFV. If NFV does not has enough resources, it rents resources from the central controller of network operators to provide services through the rented resources [133] and sends an application provision message to the application



Application service	Communication	Destination
Road safety	Vehicle-to-Pedestrian (V2P)	A person
Health-related	Vehicle-to-Infrastructure (V2I)	A building (hospital)
Entertainment-related	Vehicle-to-Vehicle (V2V)	A vehicle

Figure 8.1: Integrated cognitive radio vehicular network.

owner. Applications in this subsection include safety applications, health monitoring, and entertainment-related applications. These different VNFs are then maintained, managed, and controlled by an SDN controller. Hence, whenever a node (a vehicle, a person, or a building) wants to access one of these virtualized networks for service provision, it sends a service request message (SRM) to the SDN controller. The SDN controller checks its flow table, based on the quality-of-service requirements of the user. If it has a VNF for the user demand, it requests that VNF, receives the route, and returns a service provision message (SPM); otherwise, it communicates with NFV to launch a VNF according to the demands of the user.

Figure 8.1 shows the architecture of the integration in cognitive vehicular networks. The RSUs (signal lights in this work) and building are fog devices that are connected to the

fog cloud. The fog cloud acts as the local cloud in which the NFV infrastructure launches the VNFs according to the user′s demands, and the SDN controller oversees these launched VNFs. This means that this integration can divide the tasks into smaller ones by performing them in a local cloud instead of the central cloud in order to preserve latency. The RSUs that act as local controllers (LCs) reduce the burden of the SDN controller by keeping local, updated information about the network topology. LCs act as gateways between nodes and the SDN controller. The figure shows a small portion of the city. In a similar manner, several fog clouds for several portions of the city are connected to the centralized cloud. Here we see the advantage of integrating fog computing with SDN and NFV; that is, it brings the cloud down near edge users, and hence, reduces the response time. We consider three different scenarios for three vehicular applications in order to find a stable route between each source and destination pair. Based on these applications, three types of vehicular communications—vehicle-to-pedestrian (V2P), vehicle-to-infrastructure (V2I), and vehicle-to-vehicle (V2V)—are outlined in this work. As this is a cognitive communications network, primary users (PUs) are assumed to be sited along the roadways, as shown in Fig. 8.1. Two nodes can only communicate with each other if they have consensus about a common idle channels. In the following, we will explain each scenario one by one.

1. **Road safety:** A vehicle in a parking area wants to signal its owner about an emergency road situation, as shown in Fig. 8.1. The vehicle communicates with the nearest signal light, which forwards the request to the SDN controller in the local cloud if it does not already has a route. The SDN controller checks its forwarding table to determine if it has a route to the pedestrian, and it sends a reply message back to the signal light. If not, it sends the request message to the corresponding virtual network to which the user request belongs (e.g., a road safety application in this scenario) in order to provide a stable route from vehicle to pedestrian. At the destination, the

owner wearing a smart watch receives a signal from the smart traffic light about the road situation. Wanting to cross the road to reach the parking area, as he reaches the zebra crossing, the signal light detects his presence and sends him a signal about the emergency situation. This is an integrated vehicle-to-pedestrian communication for an emergency situation. We assume that where there is a zebra crossing, there must be a signal light. For simplicity, we do not show them at all the zebra crossings in Fig. 8.1.

2. **Health-related:** In the second scenario, an ambulance wants to signal a nearby hospital to make it aware of the current emergency situation. It sends the request message to a nearby signal light, which forwards it to the SDN controller. The SDN controller checks its forwarding table to determine if it has a route to the hospital building; if so, it sends the reply message to the signal light. If there is no route, it sends the request message to the virtual network corresponding to the user request (i.e., the health monitoring application in this scenario) to provide the service for the current situation. Finally, the route is sent by the SDN controller to the ambulance, which considers parked cars as relay nodes in this scenario as shown in Fig. 8.1. Hence, within two hops, the packet reaches the final destination.

3. **Entertainment-related:** The third demand is an entertainment-related application where both the source and the destination are moving vehicles. In a similar way, the source communicates with a nearby signal light to reach the SDN controller, and a path is sent by the SDN controller, which considers parked vehicles as relay nodes. From these scenarios, we can clearly see that parked cars are used as relay nodes for different applications. This is due to the virtualization that isolates applications running on the same nodes. The different requesting users in these three scenarios

can send requests at the same time. It is the SDN controller that checks the user demands and distributes the requests to the corresponding VNFs.

The routing path is selected using a Q-learning algorithm, which is a reinforcement-learning algorithm to solve the routing problems [136]. Q-learning is based on the value of state–action pair $Q(s, a)$ which is an updating function given as:

$$Q(s, a) = R + \gamma \sum_{s' \in S} P_{ss'} maxQ(s^{'}, a^{'}) \tag{8.1}$$

where γ is the discount factor, $maxQ(s^{'}, a^{'})$ models the maximum expected future reward, and R is the expected immediate reward. Hence, the querying node selects the next-hop node based on the following reward equation:

$$R = \beta \times (1 - \frac{1}{hello - messages/t}) + (1 - \beta)\frac{1}{TD} \tag{8.2}$$

where β is a weight factor, and transmission delay, TD, is defined as:

$$TD = \frac{r \pm d_{ij}}{max(1, \sqrt{(v_i \cos\theta_i - v_j \cos\theta_j)^2 + (v_i \sin\theta_i - v_j \sin\theta_j)^2})} \times min(Ch_1, Ch_2, ..., Ch_M) \tag{8.3}$$

where v is velocity, θ is the angle, d_{ij} is the distance, and r is the transmission range; $min(Ch_1, Ch_2, ..., Ch_M)$ represents the channel that has the highest belief in a set of idle channels between node i and node j, which has already explained in detail in chapters 2 and 5. We use max in the denominator because the parked cars and vehicles have $v = 0$, therefore, in those cases, the denominator remains one. Hence, the path is selected by choosing, hop-by-hop, the highest Q-values for each link between source and destination. The lower the value of TD, the higher is the reward. In order to make the convergence faster in a mixed (static plus mobile) environment and to reduce latency, we use (8.1) to update the Q-value.

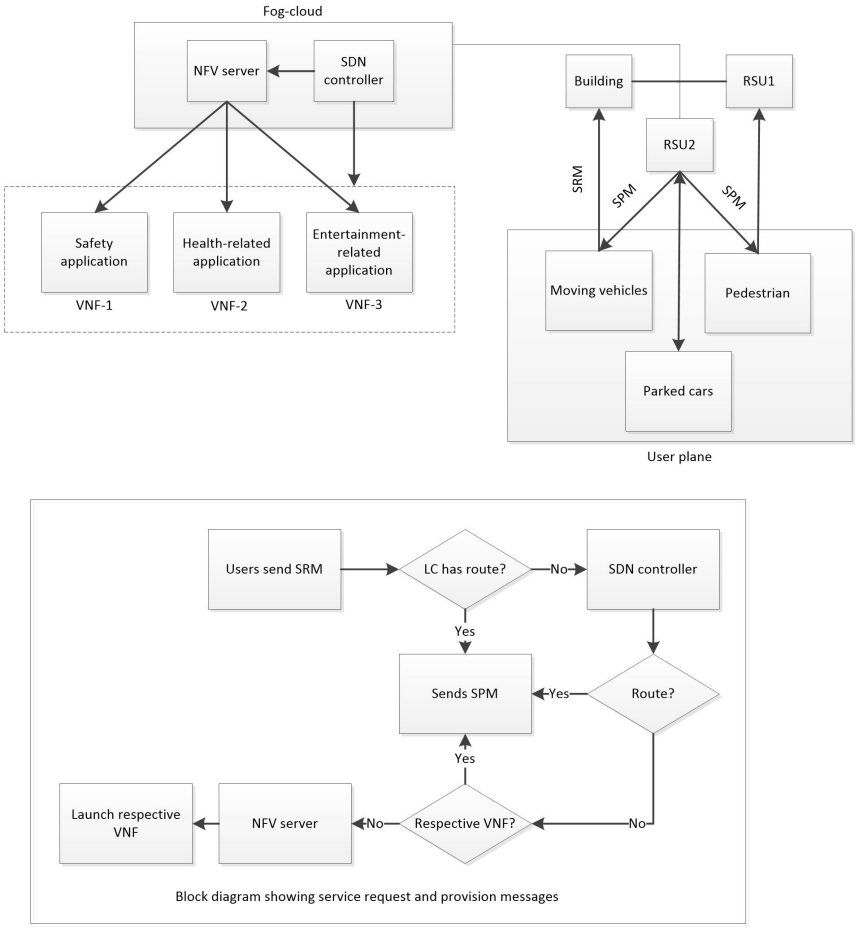


Figure 8.2: Communication among different vehicular applications in an integrated framework along with SRM and SPM flowchart.

Figure 8.2 explains the comprehensive algorithm by showing how the user benefits from the integrated cognitive vehicular network. The nodes (moving vehicles, parked cars, and pedestrians) periodically update each other and the corresponding RSUs about their current states. The exchanged information includes their IDs, positions, velocities, and channel states. The channel state represents the presence or absence of the PU. We consider cognitive radio spectrum as TV spectrum in this chapter. This updated information is exchanged between LCs and the SDN controller so that an updated local and global network topology, respectively, is maintained. Accordingly, whenever a user demands a service, it

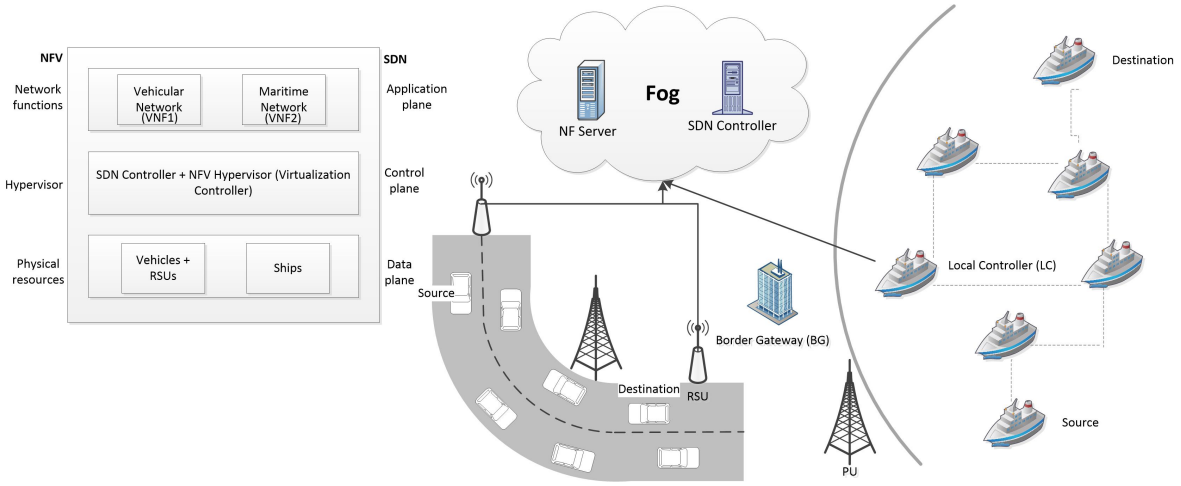


Figure 8.3: Integrated cognitive coastal city.

sends an SRM to the LC. The LC replies with the SPM if it has a route to the destination of the querying node; otherwise, it asks the SDN controller for the SPM. The SDN controller sends the SPM back to the LC if it has a route for the querying node; otherwise, it requests the corresponding VNF to provide the service if the VNF for that service was already launched by NFV. If not, it sends the SRM to NFV to launch the corresponding VNF and provide the service.

8.2.2 An integrated cognitive coastal city

An integrated cognitive radio coastal city to fulfill the service demands of citizens in less response time is shown in Fig. 8.3. The objective of this proposed architecture is to overcome major issues in different types of existing applications that consider different communications systems. We designed an integrated coastal city to serve citizens with different application demands within an all-in-one framework. For the current work, we combine terrestrial and marine applications to make an integrated coastal city. The terrestrial net-

work includes vehicular applications. The fog cloud functions as the local cloud by serving as a central entity near the edge users to provide stable links between users on ships and in vehicles. Two types of application service are launched by NFV hypervisor: vehicular applications and maritime applications. The launched virtual functions are monitored and controlled by an SDN controller. The SDN controller is also responsible for connectivity among these launched virtual functions. It keeps the global updated network topology of both networks by communicating with the local controllers (LCs) of each network. The LCs, which are roadside units (RSUs) and ships near the shore, keep the local updated topology of the corresponding network. For marine communications, we assume a ship moving close to shore is an LC. A border gateway (BG) is used to communicate between the two different networks. Like the LCs, the BG is in direct communication with the SDN controller.

As this is a cognitive coastal city, primary users are assumed to be sited along the roadways and the seashore, as shown in Fig. 8.3. For that reason, a car can only communicate with the LC and with its neighboring cars if the two communicating nodes have consensus about a common idle channel. Similarly, ships only communicate with their LC and with each other if there is a common idle channel between the two. The integration enables different users from different applications to be served at the same time. In Fig. 8.3, a vehicular source–destination pair (V2V communications) is looking for a stable route to communicate with each other. The source-car asks the LC to provide the stable route. The LC provides the route either from its forwarding table or after receiving it from the SDN controller. At the same time, a source ship at sea requests a route for a destination. This is ship-to-ship (S2S) communications where both the source and destination are moving ships. In a similar manner, the marine LC provides the route either from its forwarding table or after receiving it from the SDN controller. The cars and the ships in these two networks periodically update their neighboring nodes or the LC (if within transmission range) to

update each other with the current network state. Because of this exchange of data, all LCs in both networks are able to keep a local updated topology about the corresponding network.

Figure 8.3 also represents a special scenario where a car′s driver wants to know about the current status of a shipment on a cargo ship (i.e., the same destination ship in Fig. 8.3). This is vehicle-to-ship (V2S) communications using different environments. The car needs a stable path to the destination cargo ship, and therefore, it communicates with the nearest RSU requesting a stable path to the cargo ship. Because, the destination belongs to the marine network, the RSU directly forwards the request to the SDN controller. The SDN checks its forwarding table to determine if it can fulfill the user′s demand. If so, it quickly sends a service provision message to the car. Otherwise, it obtains the service from VNF of the marine network and provides a route for hybrid communications between the source car and the destination ship. As this is a hybrid communications route, the BG is used as a gateway between the vehicular and marine environments. The routing path is selected using the same algorithm described in previous subsection. Hence, the final route is

source car—relay car—destination car—BG—LC—relay ship—destination ship.

Figure 8.4 explains the comprehensive algorithm by showing how the user benefits from the integrated cognitive coastal city network. The nodes (moving vehicles and ships) periodically update each other and the corresponding LCs about their current state. The exchanged information is their IDs, positions, velocities, and channel states. To keep discrimination among different communicating nodes, we use v-ID, v-position, v-velocity, and v-channel for vehicular communications, and s-ID, s-position, s-velocity, and s-channel for marine communications. The channel state represents the presence and absence of the PU. This updated information is exchanged between LCs and the SDN controller, respectively,

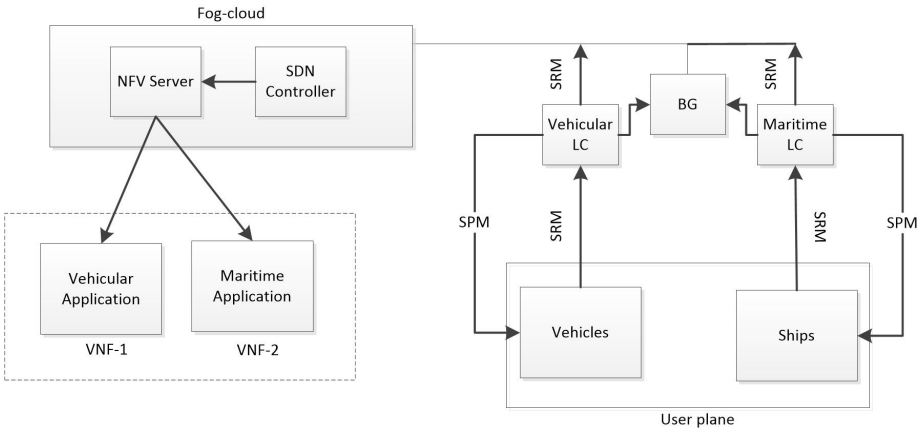


Figure 8.4: A flowchart representing the proposed coastal city architecture.

so that an updated local and global network topology is maintained. Accordingly, whenever a user demands a service, it sends an SRM to an LC. The LC replies with an SPM if it has a route to the destination of the querying node; otherwise, it asks the SDN controller for the SPM. The SPM in this chapter is a stable route calculated with (8.1). The SDN controller sends the SPM back to the LC if it has a route for the querying node; otherwise, it requests the service from the corresponding VNFs if the VNF for that service was already launched by NFV. If not, it sends SRM to NFV to launch the corresponding VNF and provide the service.

8.3 Simulation results and discussion

The performance of both integrated networks were evaluated in NS-2 . Almost same parameters were used to evaluate the two networks that were used in chapter 5 and 6. Therefore, we mention only new parameters here. For vehicular networks, we divided the network into three source nodes and three destination nodes. The pedestrian, the parked cars, and the hospital building are fixed nodes. The source vehicle and destination vehicle for the

entertainment-related application moved at a speed of 15m/s. The ambulance moved at a speed of 20m/s. However, for hybrid network, we divided the network into one vehicular source–destination pair and one marine source–destination pair. The total number of nodes moving in the hybrid network varied between 6 and 24, whereas for vehicular network, these were between 4 and 16, each having a transmission range of 200 m. Vehicles and ships moved at varying speeds up to a maximum of 15 m/s. The LC for the marine network moved at a speed of 10 m/s close to shore to keep it connected with the SDN controller. The $\beta = 0.7$, $\gamma = 0.8$, $P_{ss} = 0$, $P_{ss'} = 1$, and $\eta = 0.9$. A moderate sea state with a wave height between 1.83 m and 2.29 m [47] was used to make stability between the two environments.

Figure 8.5 shows the packet delivery ratio, the end-to-end delay, and the routing overhead ratio, respectively, as a function of the number of nodes for different vehicular applications, with different probabilities of the PU being idle as a parameter. The packet delivery ratio for all the application services increases with an increasing number of nodes in the network. The fog cloud improves network performance in terms of delivery ratio because of the logically centralized controller that dictates the behavior of the network. However, the delivery ratio of road safety application is high, compared to the other two scenarios. This is because of network stability due to the large number of fixed nodes. Similarly, with an increasing number of nodes in the network, the delay decreases. The delay is high for the entertainment-related service, because both the source and destination are moving vehicles. Similarly, the health-related service has a fixed destination; therefore, performance is comparatively better than the entertainment-related service. Among the three services, road safety performs better than the other two, even when the number of nodes is lower. This is because both the source–destination pair is fixed, and the relay nodes (parked cars) are also fixed. From the figure, we can see that the routing overhead ratio increases with an increase in the number of nodes and with a decrease in idle probability for all the scenarios.

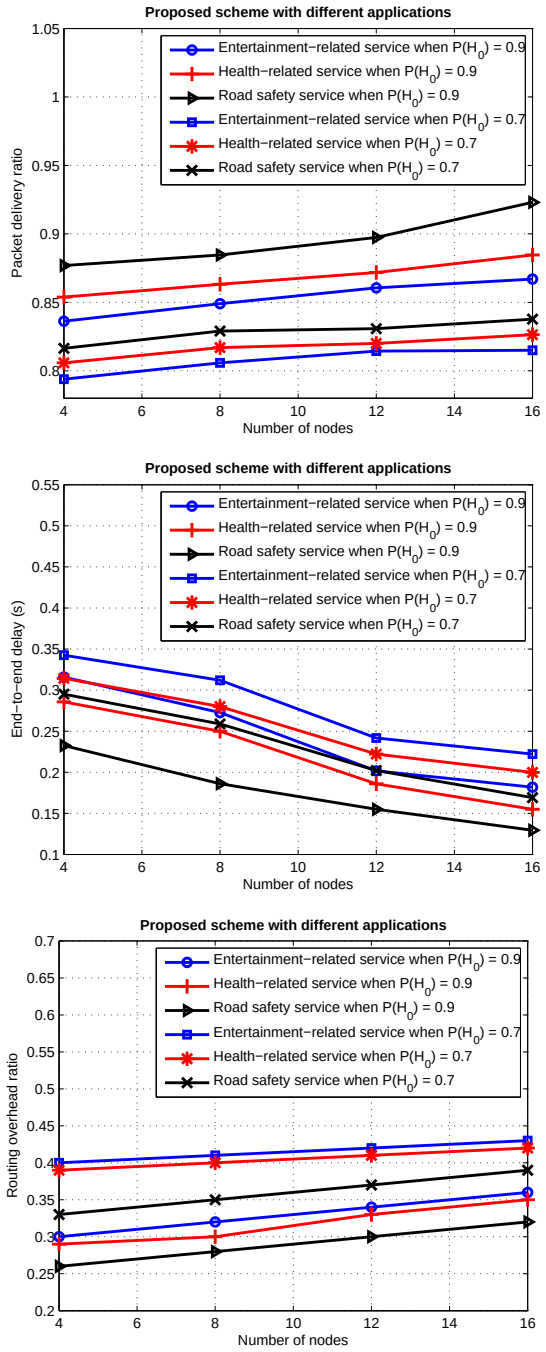


Figure 8.5: Performance comparison between the three vehicular application scenarios in terms of (a) packet delivery ratio; (b) end-to-end delay; and (c) routing overhead ratio.

However, the overhead ratio of the road safety application shows better performance than the other two application services. This is due to having fixed nodes, which reduces the chances of link fragility, thereby reducing the number of control messages in the network.

Figure 8.6 shows the packet delivery ratio, the end-to-end delay, and the routing overhead ratio, respectively, as a function of the number of nodes for different communications systems, with different probabilities of the PU being idle as a parameter. The packet delivery ratio for all the communications systems increases with an increasing number of nodes in the network. The pattern is the same for hybrid and pure communications, i.e., when increasing the number of nodes and increasing the probability of the PU being idle, the ratio increases. The delivery ratio of V2S communications is high, compared to other two communications systems when the number of nodes is high. This is because of the fog cloud that maintains stability between the two environments. The S2S performance is poor because of the constantly changing sea surface. Similarly, the delay is high for the S2S communications, because of the environmental factor. This means that with the changing positions of ships in a marine environment, the sea surface is also changing constantly and, therefore, results in more fragile links than in terrestrial networks. Moreover, hybrid communications shows better performance due to its hybrid nature, i.e., the path is divided into two types of network. For that reason, the SDN controller is responsible for providing more stable paths with the help of the BG. Similarly, the overhead ratio of V2S communications shows better performance, compared to the other two communications systems. This is because the BG and LCs reduce the chances of link fragility, thereby reducing the number of control messages in the network. Moreover, selecting the most stable route between source and destination at the controller by maximizing the reward reduces overall network overhead. A complete analysis of our simulation results shows that network performance varies with the type of communications system, the type of environment (terrestrial or marine),

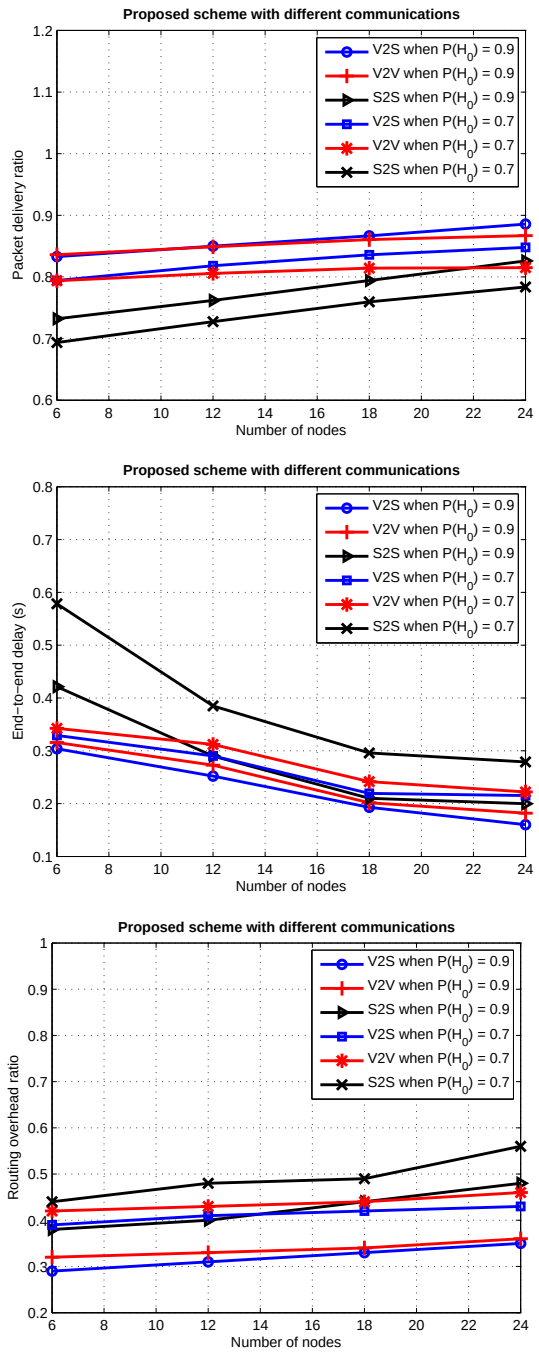


Figure 8.6: Performance comparison between the proposed hybrid and pure communications in terms of (a) packet delivery ratio; (b) end-to-end delay; and (c) routing overhead ratio.

and also the type of relay nodes.

8.4 Chapter summary

In this chapter, a novel integrated, cognitive vehicular network for different vehicular application scenarios, and a novel integrated cognitive coastal city for both hybrid and pure communications between vehicular and maritime networks are proposed. The idea of integrating software-defined networking, network function virtualization, and fog computing in a cognitive routing schemes for different networks makes this integrated frameworks unique. Three virtual networks for three vehicular applications and two virtual networks for each vehicular and maritime application are launched by NFV based on the user demands, and the SDN controller is responsible for controlling and managing these virtual networks. Vehicle-to-ship communications is introduced to provide efficient and reliable services to users on different network systems of coastal smart city. Routing is the service provided by the virtual networks, where the SDN controller provides a stable path between each source–destination pair for each querying node. The idea is to facilitate citizens′ demands for services from different applications under the same infrastructure.

Chapter 9

Conclusion and future directions

9.1 Conclusion

Ubiquitous wireless communications is an essential goal for numerous applications ranging from traffic safety to entertainment-related information for various users either on the land, the sea surface or in the ocean. The dedicated licensed spectrum for each of these communications systems has been found insufficient to fulfill the increasing needs of vehicular, maritime, and underwater applications. To alleviate the spectrum scarcity in these networks, cognitive technology is a viable solution as it can utilize spectrum in an environment-friendly manner (i.e., avoiding harmful interference with licensed users). Hence, the stable links are essential for communications with different users in order to meet the growing demands of vehicular, maritime, and underwater applications. Therefore, this dissertation proposed novel cognitive routing protocols for each of these networks to ensure cooperation among the respective users by retaining stable links for vehicular, maritime, and underwater communications. We first proposed cognitive routing protocols for each of these networks with and without SDN approach to ensure stable routes between sources and destinations in order to overcome the problems of spectrum scarcity and high latency in vehicular, mar-

itime, and underwater networks, respectively. We then introduced the novel integrated cognitive networks to fulfill the demands of different users for different applications under the same infrastructure. We ended up this dissertation opening a new door for designing a coastal smart city for cognitive vehicular and maritime networks by integrating software-defined network, network function virtualization, and fog computing. In the following, we summarize the major contributions of this dissertation.

9.1.1 Conventional cognitive routing protocols

We first combined both channel selection and relay selection in a vehicular communications network to propose a novel hybrid cognitive routing scheme for both highway and city scenarios by considering both V2V and V2I communications. The RSU serves as a storage device to enhance spectrum availability by providing channel information for future segments in advance, and it functions as a relay node under sparse network conditions. The results of this proposed scheme show better performance for end-to-end delay, packet delivery ratio, and routing overhead ratio. To propose a novel scheme for cognitive maritime ad hoc networks, we then combined both channel selection and path selection in marine environment. This is ship-to-ship cognitive routing technique where channel selection is done by the cooperation of maritime users and selection of path is achieved by two well-known routing protocols AODV and GPSR to test the validity of the proposed protocol in both flood-based and geographical routing protocols. The results of this cognitive maritime scheme show that AODV outperforms GPSR in all cases except the one when all ships are moving with the same direction to the destination (an exceptional case). Moreover, this scheme shows better performance for average path duration when the sea state is calm and when ship density is high in the network. Furthermore, to ensure cooperation among acoustic users and to retain link stability for underwater communications, we proposed a novel

routing scheme for underwater cognitive sensor networks. Both natural acoustic systems and artificial acoustic systems are considered PUs in this scheme. The results of this scheme show better performance for average delay, packet delivery ratio, and overhead ratio.

9.1.2 SDN-based cognitive routing protocols

Software-defined networking is an emerging technology that increases network intelligence by separating the control plane from the data plane. SDN enhances network compatibility by reducing forwarding delay as this new paradigm eliminates the need for hop-by-hop flooding at each intermediate node while discovering a route. Existing networks on the land, the sea surface and in the ocean need a new candidate to improve network performance and communications reliability. Therefore, we then proposed novel routing protocols for cognitive radio software-defined vehicular networks, for cognitive radio software-defined maritime networks, and for cognitive acoustic software-defined underwater networks to make stable routes with the minimum durations. The idea of combining a cognitive capability with routing schemes in software-defined vehicular, maritime, and underwater networks makes these protocols unique. A main controller is responsible for network management, while several local controllers are used to reduce the number of control messages and any network delay. For vehicular communications, the local controllers are RSUs, for maritime communications, these are cluster heads of each fleet, and for underwater communications, autonomous underwater vehicles are used. The results of all these schemes show better performance for average delay, packet delivery ratio, and routing overhead ratio.

9.1.3 Integrated cognitive routing protocols

Finally, we opened a new door for routing in cognitive networks by integrating software-defined networking, network function virtualization, and fog computing. The idea of in-

tegration in cognitive networks is to find stable routes from sources to destinations for different applications in different networks. Routing is the service that is provided by these virtual networks where the SDN controller provides the stable paths between each source-destination pair to each querying node. The idea is to facilitate different users demanding service for different applications under the same infrastructure. We first proposed a novel integrated cognitive vehicular network that fulfills the demands of each application user for three different vehicular applications in this study. These different vehicular applications are provided with the same stable paths due to integration. We then ended up this dissertation by designing a novel integrated cognitive coastal city by combining vehicular and marine applications to fulfill the service demands of the citizens. A border gateway is used as a communicating device between the two networks. We reveled from the results of these integrated systems that network performance varies with the type of communications systems, the type of environments (terrestrial or marine), and also the type of relay nodes.

9.2 Future work

The research carried out in this dissertation suggests several interesting future directions that need to be explored further. In the following, we highlight some of them.

- A hybrid network for maritime and underwater communications can be proposed with the integration of software-defined networking, network function virtualization, and fog computing to cope with the inevitable increase in data traffic and to simplify network management by making network efficient, faster, and flexible. Similarly, SDN-based hybrid maritime and underwater communications can be established to reduce network latency and improve cooperation among different users. Moreover, a conventional hybrid cognitive routing protocol is required to forward the information

directly to the central controller on the land rather than on the sea surface.

- For sensing channels and then selecting relay, a large amount of energy is required in the proposed scheme. As these are cognitive routing schemes, therefore delay is a key component that has greater impact on the network performance because channel sensing affects the sensing time. Consequently, it is an urgent problem to consider a good trade-off among energy consumption, overhead, and delay for cognitive routing schemes based on traffic and energy balancing. Also, energy harvesting techniques, such as harvesting energy from radio and acoustic links to recharge sensors/ASV/AUV batteries, should be considered to prolong the network lifetime.

- This study considered different communications systems to propose cognitive routing protocols and a hybrid network for vehicular and maritime communications to propose an integrated coastal city. As the vehicular and the maritime communications use the same spectrum, therefore in an actual sense, the communication is not hybrid, only the environments make it hybrid. Satellite networks have gained a significant attention in academia due to their superior capacity of coverage and broadband broadcast. Therefore, we intend to propose a flexible architecture in future with heterogeneous satellite-terrestrial-maritime networks to solve a number of serious problems and achieve more better performance.

- As the proposed schemes are cognitive routing schemes, the availability of common idle channel is an elementary aspect. Increasing the neighboring size increases the availability of channel. The higher the number of neighboring nodes, the higher the querying node has chance to select a node with the same idle channel. Restricting the neighboring size degrades overall network performance due to not having common channel. However, increasing the network density in these proposed schemes

increases the redundant packet transmission and the high energy consumption. Both are challenging open research issues in cognitive networks, especially in underwater networks.

- The service provided by virtual networks proposed in this dissertation is routing only for same and different applications where the SDN controller provides the stable path between each source-destination pair to each querying node. These applications along with services for different network domains are needed to be considered in real environments. In addition, the real deployment in cognitive vehicular, maritime, and underwater networks to test our solutions is another open research issue. We have left these research issues for future work.

Publications

International journal papers

[1] Huma Ghafoor and Insoo Koo, "Infrastructure-aided hybrid routing in CR-VANETs using a Bayesian Model", *Wireless Networks*, pp. 1-19, 2017. Available online: https://doi.org/10.1007/s11276-017-1624-9

[2] Huma Ghafoor and Insoo Koo, "CR-SDVN: A Cognitive Routing Protocol for Software-Defined Vehicular Networks", *IEEE Sensors Journal*, vol. 18, no. 4, pp. 1761-1772, Feb. 2018.

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Journal papers under review

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[9] Huma Ghafoor and Insoo Koo, "A Cognitive Radio Software-Defined Vehicular Network with Fog Computing and Network Function Virtualization for Smart Cities", submitted to *Wireless Networks*, 2018.

[10] Huma Ghafoor and Insoo Koo, "An Integrated Cognitive Radio Network for Coastal Smart Cities", submitted to *IET Communications*, 2018.

International conference papers

[11] Huma Ghafoor and Insoo Koo, "Software-Defined Networking-Based Cognitive Routing Protocol for Vehicular Ad Hoc Networks", *2017 International Conference on Circuits, System and Simulation, (ICCSS-2017)*, London, UK, pp. 162-166, July 14-17, 2017.

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